UNIVERSITY OF TECHNOLOGY SYDNEY

Factors Driving Individuals' Usage Intention of Artificial Intelligence (AI) Assistants in E-commerce: Perspectives of Users and Non-Users

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Certificate of Original Authorship

I, Ahlam Alnefaie, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

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List of Publications

The following research papers were published from work undertaken by the author during this PhD research study.

- Alnefaie, A., Gupta, D., Bhuyan, M. H., Razzak, I., Gupta, P., & Prasad, M. (2020). End-to-end analysis for text detection and recognition in natural scene images. In *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1–8). IEEE.
- Alnefaie, A., Singh, S., Kocaballi, B., & Prasad, M. (2021). An overview of conversational agent: applications, challenges, and future directions. In *17th International Conference on Web Information Systems and Technologies*.
- Alnefaie, A., Singh, S., Kocaballi, A. B., & Prasad, M. (2021). Factors influencing artificial intelligence conversational agents usage in the E-commerce field: A systematic. In *Proceedings of the ACIS*.
- Bin Sawad, A., Narayan, B., Alnefaie, A., Maqbool, A., Mckie, I., Smith, J., & Kocaballi, A. B. (2022). A systematic review on healthcare artificial intelligent conversational agents for chronic conditions. *Sensors*, *22*(7), 2625.
- Alnefaie, A., Singh, S., Kocaballi, A. B., & Prasad, M. (2021). Investigating Consumer Usage Intention of Conversational AI Agents. In *Proceedings of the* ANZMAC.
- Alnefaie, A., & Kyeong, K. (2023). Cultural Transformations of E-commerce Consumer Behaviour and Intention Toward Using Artificial Intelligence (AI) Assistants. *In 57th Annual Hawaii International Conference on System Sciences, HICSS 2024 (HICSS).* [Accepted for Publication].
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Abstract

The ongoing revolution of e-commerce has brought about significant transformations in the global retail landscape, redefining how consumers interact with online platforms. In response to this transformative trend, businesses increasingly adopt and integrate artificial intelligence (AI) technologies, particularly AI assistants. AI assistants have gained significant traction to enhance customer engagement, improve personalised experience, and streamline various aspects of the e-commerce process. Companies across diverse industries and geographical regions have recognised the potential of AI assistants in fostering more profound connections with customers, providing real-time support, and bolstering sales through intelligent recommendations. Consequently, investment in AI research and development has surged, leading to remarkable advancements in AI assistants' features and functionalities. Despite the growing interest of the scientific community and business stakeholders in the topic, scholarly research on the factors influencing e-commerce consumers' attitudes and intentions toward using AI assistants is still limited and provides contradictory evidence regarding some factors. Moreover, no comparative studies in the e-commerce context empirically investigated the attitudes of non-users and users toward AI assistant use. Also, several consumers' demographics have been excluded from prior research, with no previous empirical research on AI assistant use across different cultural backgrounds.

For these reasons, the study aimed to comprehend the factors influencing consumers' behavioural intention to utilise AI assistants and to recognise the significant user differences based on multiple perspectives. This study employed a unique research model based on the technology acceptance model. It extended it with external factors of AI assistants' capabilities that still need to be tested together in AI assistant adoption for e-commerce consumers. This research conducted a mixed-method approach. In the first phase (Phase A), a quantitative method was employed to investigate the relationships between the constructs in the study model, and the Partial Least Square Structural Equation Modelling (PLS-SEM) and several statistical techniques were adopted. Furthermore, to account for cross-cultural differences and identify potential variations in usage intentions towards using AI assistants between Eastern and Western cultures, a multi-group analysis (MGA) was conducted. In the second phase (Phase B), a qualitative approach was conducted by applying machine learning and natural language processing techniques to analyse reviews of the Louis Vuitton brand's e-commerce applications. The objective of this stage was to obtain supporting evidence for the results of the

first study and to gain deeper insights into consumer attitudes and experiences. Subsequently, the results were integrated to provide multiple insights to answer the research questions and strengthen the findings.

This study has confirmed some previous studies' results and provided new findings. The attitude factor was the significant predictor of the intention to use AI assistants in non-users and users, with a direct and positive effect. Perceived usefulness was found to be the statistically significant predictor of attitudes in both non-users and users of AI assistants. The additions to the original TAM model, specifically incorporating interactive communication and personalisation, were statistically significant predictors of the attitudes of non-users and users to use AI assistants with positive effects. In contrast, perceived ease of use was a non-significant predictor of the non-users' attitudes and positively impacted the users' attitudes towards using AI assistants. Furthermore, no significant differences existed in the relationships among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultural groups.

This study contributes to both theory and practice by extending the TAM model with two external factors enabling the assessment of the factors affecting the intention to use AI assistants from consumer, social, and marketing perspectives and providing new empirical data on this topic in technology adoption studies. The study also enables further research on this topic and comparing study results, thus improving understanding of the phenomenon. It also provides various e-commerce practitioners with valuable information and recommendations regarding AI assistant use, enabling them to make better decisions in developing and implementing AI assistant technologies.

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List of Abbreviations

AI: Artificial intelligence

ALICE: Artificial Linguistic Internet Computer Entity

AT: Attitude

E-commerce: Electronic Commerce

MGA: Multi-Group Analysis

ECA: Embodied Conversational Agents

FAQs: Frequently Asked Questions

HCI: Human-Computer Interaction

ICOM: Interactive communication

IS: Information Systems

ML: Machine Learning

MTurk: Mechanical Turk

PERS: Personalisation

PEU: Perceived Ease of Use

UI: Usage Intention

PLS-SEM: Partial least squares structural equation modelling

PU: Perceived Usefulness

TAM: Technology Acceptance Model

NLP: Natural Language Processing

TRA: Theory of Reasoned Action

UTAUT: Unified Theory of Acceptance and Use of Technology

SET: Social Exchange Theory

LDA: Latent Dirichlet Allocation

NLTK: Natural Language Toolkit

TF-IDF: The Frequency Inverse Document Frequency

SD: Standard Deviation

SE: Standard Error

AVE: Average Variance Extracts

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Chapter 1. Introduction

This chapter provides an introductory overview of the research background, encompassing various elements essential to the study (1.1), and addresses the research purpose and objectives (1.2) and the research questions (1.3). Moreover, the significance of this study is expounded, highlighting its relevance in both academic and practical contexts (1.4). Section (1.5) provides the definition of key terms. In addition, the literature review and method adopted for data collection and analysis are also introduced (1.6) and (1.7), and finally, the overall thesis layout is presented (1.8). Section (1.9) concludes with a concise summary of the main points covered in the chapter.

1.1 Research Background

Artificial intelligence (AI) is becoming a more popular tool for solving commercial difficulties, such as e-commerce, by utilising natural language processing, machine learning, and deep learning algorithms. Many sectors are turning to AI to develop new communication methods with and engage customers (Libai et al., 2020). Recent text recognition and natural language processing developments have significantly influenced AI and text analytics (Mah et al., 2022). Chatbots, or AI assistants, are examples of AI systems that provide natural language user interfaces that stimulate human-human conversation. These AI assistants use text-based or voice-based inputs and outputs and are integrated into social media platforms or websites. Moreover, AI assistants, formerly offered as a customer care solution in travel, banking, and retail e-commerce, are now being utilised to engage customers in online shopping. Many retailers also adopt AI assistants to provide customer service and customised online experiences (Chung et al., 2020). For example, Louis Vuitton has introduced a chatbot that delivers information about stores, products, and customer service (Fernandes, 2020). These AI assistants, which rely on machine learning and AI algorithms, can provide the required information quickly and directly. From the customers' perspective, AI assistants enable convenient customer service and customised interaction without downloading an app (Akhtar et al., 2019). As a result, experts anticipate that enterprises will produce more AI assistants than traditional mobile apps (Brandtzaeg & Følstad, 2018). Furthermore, Insider (2020) predicts that conversational agents will save $11 billion by 2023. According to Jovic (2020), business experts estimated that by 2022, 90% of bank customer interactions will be handled without human agents and with developing technologies such as machine learning applications and chatbots. This anticipation is supported by a recent development in the environment, in which face-to-face interaction with human agents became inaccessible during the COVID-19 pandemic. That is why customers now rely on social networking sites and online communication applications such as AI assistants to seek information about purchasing products and contacting brands for customer service.

Despite AI assistants' various roles and capabilities and the increasing attention from researchers and practitioners towards their adoption, the scholarly investigation concerning the determinants of consumers' behavioural intention to use AI assistants in e-commerce has been notably constrained and insufficient (Jain et al., 2022). Moreover, it is noteworthy that previous studies examining the adoption of AI assistants have predominantly relied on theoretical models that overlook essential aspects such as social communication skills and personalised services and provided conflicting findings regarding certain factors influencing the use of AI assistants (Go & Sundar, 2019; Nordheim et al., 2019; Liew et al., 2021). At the same time, social presence influences consumers' trust in AI assistant usage (Toader et al., 2020), and communication competence does not affect customer satisfaction (Chung et al., 2020). Also, previous studies in AI assistant acceptance were mainly conducted in specific cultural contexts (Sindermann et al., 2022), limiting the applicability of their findings to other cultural contexts. On the other hand, although cross-culture research is interesting for global insights, empirical research has yet to be conducted on cross-culture analysis for AI assistant adoption in e-commerce (Perifanis & Kitsios, 2023; Bawack et al., 2022).

In the case of the e-commerce context, Oguntosin and Olomo (2021) and Syarova (2022) conducted the adoption of chatbots in the context of online shopping. Still, they collected data from only users and suggested other studies to focus on nonusers. Følstad and Brandtzaeg (2020) pointed out a lack of studies focusing on users unfamiliar with AI assistants in customer services. Moreover, no comparative studies in e-commerce consumer research empirically investigated the attitudes of users and non-users toward AI assistants called chatbots (Følstad & Brandtzaeg, 2020). Therefore, this study examines the factors affecting users' and non-users' attitudes toward adopting AI assistants for Western and Eastern e-commerce' consumers. Understanding users' differences may assist enterprises and organisations seeking to introduce new technology and modify their marketing and outreach activities to better align with their target audience's needs (Choi et al., 2014).

From a practical point of view, the significance of AI assistants lies in their capacity to enhance the interaction between companies and customers through diverse marketing initiatives. Therefore, assessing consumers' perceptions of AI assistants becomes imperative, as these perceptions can significantly impact their intention to use such technology. While there is an abundance of research focusing on the technical aspects of AI assistants, there remains a need for further investigation into the acceptance and consumer behaviour concerning the adoption of AI assistants (Cheng & Jiang, 2021; Chung et al., 2020). Moreover, the investigation of adoption behaviour, with a particular emphasis on usage intention, is the leading research direction for many information system and marketing scholars due to its consideration of usage intention as a reliable assumption of practical technology usage (Al-Adwan et al., 2023; Zhang et al., 2021). While usage intention is defined as individuals' intention to utilise the information system (Bhattacherjee, 2001), based on this definition, the usage of AI assistants refers to the extent to which a consumer intends to use the AI assistants. The initial development of AI assistants was based more on technology capabilities than on market aspects; thus, customers' adoption of AI assistants has been relatively limited since customer perceptions and demands were not effectively addressed (Zierau et al., 2020; Zarouali et al., 2018). Usage intention, in particular, is frequently recognised in the literature as a predictor of new technology efficacy and leads to improved consumer behaviour about the latest technology (Al-Adwan et al., 2023; Liao et al., 2009).

Meanwhile, due to COVID-19, consumers spend more time online, driving firms to adopt new digital strategies for connecting with loyal customers. This challenge has compelled organisations to devise or find innovative solutions to adapt to the new environment. Lockdowns and social distancing measures have disrupted consumer behaviour worldwide, driving businesses to seek new methods to engage with consumers locked at home and re-establish their market position (Sharma & Jhamb, 2020). As consumers integrate new digital technologies into their isolated lifestyles, their shopping habits and daily routines change (Ali, 2020). Overall, the current study sheds light on the evolving role of AI assistants in e-commerce and helps businesses make informed decisions about the design of this technology to meet consumers' changing needs and preferences.

As AI continues to transform the landscape of online shopping, understanding the drivers behind consumers' decisions to engage with AI assistants is crucial for businesses and policymakers alike. Recently, AI-powered assistants have gained popularity in e-commerce, offering personalised and efficient customer experiences. However, despite their growing prominence, there needs to be more understanding of how consumers' usage patterns may shape their acceptance and adoption of AI assistants. Also, recognising and comparing cross-cultural consumers will provide valuable insights into tailoring AI-based services to suit diverse consumer preferences, ultimately enhancing user satisfaction and loyalty.

This research will employ a comprehensive and multi-dimensional approach to investigate the attitudes, usage intention, and perceptions of e-commerce users towards AI assistants in both Western and Eastern contexts. Therefore, the study aims to comprehensively understand the factors that influence behavioural intention to use AI assistants among non-users and e-commerce users. The findings of this study will offer actionable recommendations to businesses and e-commerce platforms seeking to implement AI assistants, ensuring their strategies are attuned to consumers' specific preferences and expectations. Additionally, from an academic standpoint, this research will contribute to the growing body of knowledge concerning the factors that influence consumers' attitudes and behavioural intentions regarding AI assistant usage to ensure the further development of AI assistants that can lead to successful marketing and commercial objectives.

1.2 Purpose and Objectives of this Study

The previous section discussed the study's research background and identified research gaps. This section addressed the study's research purpose and objectives. Given the increased adoption of AI assistant applications, this study aims to investigate and comprehend the factors influencing the attitudes and usage intention of AI assistants across users and non-users, as well as to establish a conceptual framework concentrating on cultural differences in the relationships between influencing factors, attitudes, and behavioural intention in the context of e-commerce. However, some online purchasers still need to trust the capabilities of AI assistants (Uysal et al., 2022). The development of new technologies that aim to provide services to global consumers must include a consumer-centric approach (Zhang et al., 2021). In this context, the study aimed to achieve multiple objectives:

- To explore key factors influencing the intention towards adopting AI assistants in e-commerce by developing a unique research model through extending the technology acceptance model for adopting AI assistants in E-commerce.

- To empirically examine the model using both quantitative and qualitative methods to determine which factors significantly influence the intention of users and non-users to continue using AI assistants in the context of e-commerce.
- To examine the potential variations in the relationships among the primary factors influencing the intention to use AI assistants across two cultural contexts to understand their attitudinal differences towards AI assistant adoption. This aims to augment the theoretical comprehension of this subject and provide insights into optimising the design of AI assistants to accommodate diverse preferences, ultimately contributing to heightened customer satisfaction.

The rapid advancement of AI technology has led to a proliferation of AI-powered assistants in the e-commerce domain, significantly transforming how consumers interact with online platforms. These AI assistants offer personalised recommendations, enhanced customer support, and streamlined purchasing processes, among other benefits. The motivation behind this research is multi-fold, including addressing a gap in the literature, enhancing e-commerce strategy, cross-cultural insights, and academic contribution. Even though this study did not cover major differences between the two cultural groups, it's still really important to consider how culture affects AI technology use (Chi et al., 2023). Investigating the factors that influence consumers' behavioural intention to use AI assistants in a cross-cultural context holds significant theoretical and practical implications. It will advance scholarly understanding and provide valuable insights for e-commerce businesses and technology developers striving to create inclusive and user-centric AI assistant solutions. While AI's technological aspects have garnered significant attention, a comprehensive understanding of its social and marketing dimensions is essential for harnessing its full potential. The primary motive for the research was to integrate AI's social and marketing perspectives, shedding light on its impact on consumer behaviour and usage decisions. From a social perspective, this study explored how interactive communication shapes consumers' interactions, attitudes, and usage decisions to start and continue using this technology. From a marketing perspective, this study investigated how personalised marketing efforts of AI assistants influence consumers' attitudes towards using AI assistants.

An additional factor intensifying the motivation for undertaking this investigation is the absence of comprehensive empirical studies into this subject matter, considering both the perspectives of users and non-users. Previous researchers have presented in a number of studies contradictory results about the influence of certain factors among users. Følstad and Brandtzaeg (2020) noted a lack of studies focusing on unfamiliar users with AI assistants. Another motive for this research is to discover the crucial cross-cultural differences between Western and Eastern consumers. Exploring diverse cultures is crucial because culture plays a big role in shaping people's thoughts about and acceptance of technology. This study focuses on Western and Eastern consumers for several reasons. Firstly, Western and Eastern cultural identities and profiles are significantly different. Secondly, within the scope of cultural perspectives, it is notable that Western culture places a greater emphasis on explicit knowledge and tangible, individualistic motivational factors, in contrast to Eastern cultural views that lean towards valuing tacit knowledge and abstract principles (Jelavic & Ogilvie, 2010). Thirdly, Eastern consumers prefer a high-context communication pattern, while Western consumers prefer a low-context one (Liao et al., 2008). Conducting cross-cultural research helps global business practitioners identify differences in cultural attitudes towards adopting AI assistants. This, in turn, empowers them to refine strategies for developing AI assistants that better suit diverse markets.

Dwivedi et al. (2021) demonstrate that technology developers need adequate insights concerning the social-cultural factors that might influence how end-users interact with AI. The global reach of e-commerce businesses implies that AI assistants interact with a diverse population with different social and cultural backgrounds (Balakrishnan & Dwivedi, 2021). Therefore, understanding the cultural differences and similarities that emerge among the target consumers can be instrumental in developing AI solutions that can adequately enhance online business outcomes by effectively meeting the expectations of each customer. According to Zhang et al. (2021), AI assistants can be instrumental in enhancing marketing capabilities in e-commerce. In line with these sentiments, Davenport et al. (2020) suggest that strategic marketing involves market research that covers the cultural characteristics of the target population. As a result, understanding the impact different cultures have on the use of AI assistants can help enhance the marketing strategies adopted with the application of such technologies in e-commerce.

1.3 Research Questions

Although the AI assistant literature has seen significant advancements, notable research gaps remain in understanding the factors influencing AI assistant usage and their implications on consumers' attitudes and adoption of e-commerce. The main research question of this study is:
Main Research Question: What factors influence individuals' intention to use AI assistants in e-commerce among users and non-users, and are there significant differences in these factors' impact when comparing Western and Eastern cultures?

The main research question has been subdivided into several sub-questions as follows:

> *RQ1.1: How does perceived usefulness affect the attitudes of users and non-users towards using AI assistants in e-commerce?*
>
> *RQ1.2: How does perceived ease of use affect the attitudes of users and non-users towards using AI assistants in e-commerce?*
>
> *RQ1.3: How does perceived ease of use affect the perceived usefulness of users and non-users of AI assistants in e-commerce?*

RQ1.4: How does interactive communication affect the attitudes of users and non-users towards using AI assistants in e-commerce?

RQ1.5: How does personalisation affect the attitudes of users and non-users towards using AI assistants in e-commerce?

RQ1.6: How does attitude affect the intentions of users and non-users towards using AI assistants in e-commerce?

RQ1.7: Do significant differences exist in the relations among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultures?

1.4 Significance of this Study

The rapid advancement of AI technology has significantly transformed and impacted various aspects of society, including how consumers interact with online platforms. As AI assistants become more widely integrated into e-commerce platforms, specifically text-based AI assistants known as chatbots designed to provide overall customer support in the fashion industry, it is essential to understand the key factors influencing and driving consumers' intention towards their use. AI technologies are seen, expected, and accepted differently in different consumers' experiences and technological skills. Therefore, investigating the users' differences in consumer behaviour and intention concerning AI assistants can provide valuable insights into the complicated interplay between technology and consumer research. By exploring the important aspects that influence attitudes and usage intention, this research sheds light on the underlying factors that drive consumers' attitudes towards using AI assistants in e-commerce. Understanding how consumer beliefs, perceived usefulness, and perceived ease of use affect consumer attitudes can assist e-commerce businesses in developing solutions that are tailored to specific consumer preferences and expectations.

Additionally, investigating the relationship between AI features in interactive communication and personalisation, consumer attitudes, and intentions towards AI assistants is also crucial. As the pandemic has accelerated the adoption of online platforms and increased reliance on online shopping, limited research has been conducted on the factors affecting users' and non-users' evaluation of AI assistant system performance (satisfaction and adoption) in e-commerce (Song et al., 2019). Meanwhile, understanding the differences between Eastern and Western cultures is crucial when investigating the research questions on e-commerce consumers' behavioural intention towards using AI assistants. The significance lies in recognising that cultural variations can significantly influence consumers' attitudes, perceptions, and preferences, thus shaping their adoption of AI assistants in e-commerce. By investigating different types of customers, researchers can find the differences in customers' attitudes towards AI adoption or resistance to using AI assistants and provide valuable insights for new or potential users.

Moreover, by considering cultural nuances, researchers can identify how these factors may differ or align between Western and Eastern consumers, providing valuable insights for businesses to tailor AI assistant experiences that resonate better with specific cultural contexts. Investigating whether a distinct variation exists in the intention to use AI assistants between the two groups of consumers helps to address potential disparities in their acceptance and utilisation. In essence, comprehending Western and Eastern consumers' differences enhances the applicability of research findings, facilitating the development of more effective strategies for e-commerce businesses and marketers in respective regions. This understanding can provide insights into strategies for effectively addressing consumer concerns and promoting positive experiences with AI assistants. Hence, this study explores various factors impacting customers' attitudes towards AI assistants employed within e-commerce platforms, encompassing websites, mobile applications, or social media sites.

The current study is significant in developing a comprehensive understanding of how the broad Western and Eastern cultures influence the use of AI assistants as a marketing strategy in e-commerce. According to Song et al. (2018), customers from different cultural backgrounds present varying reception to marketing strategies. Cornali and Tirocchi (2012) and Ding and Saunders (2006) show that the transition to digital technologies and the diffusion of cultures influenced by increased socialisation and the globalisation phenomenon has led to the emergence of an international culture. As a result, there are many commonalities among online users that foster the deployment of technologies that have similar features in the global e-commerce ecosystem. The insights gained from the current study will help to demonstrate if the differences among cultures call for variations in the AI solutions deployed in e-commerce when targeting a culturally diverse customer base. Additionally, these insights can highlight the social and technical implications in the development, implementation, and use of AI assistants in e-commerce.

This study significantly contributes to multiple interdisciplinary knowledge domains, including consumer culture, marketing science, information systems research, engineering, and design. The research delivers the following valuable insights, enriching the existing body of knowledge in these diverse fields. This contribution makes several significant contributions to conversational AI assistants and their use in e-commerce.

1. It investigates state-of-the-art conversational AI assistants, providing valuable insights into their capabilities and limitations.
2. The contribution presents a centric customer assessment framework to measure customers' attitudes toward using conversational assistants for e-commerce. This unique framework provides a valuable tool for developers and marketers looking to assess the effectiveness of their conversational assistant technology.

3. It provides new empirical data on the cross-cultural investigation for AI assistant adoption while presenting a sound basis for further research into different cultural factors.
4. This research provides insights for developers and designers interested in developing AI assistants for successful marketing and business objectives. These insights guide the development of conversational assistants that meet the needs of both businesses and customers.
5. This contribution provides valuable insights for online retailers and marketers looking to develop online experiences incorporating conversational assistants as a customer service and practical communication application.

1.5 Definition of Key Terms

AI assistants. They are also known as chatbots or virtual assistants. Maedche et al. (2019) describe AI assistants as software applications that leverage AI technologies to foster interactive and personalised services. According to Mekni (2021), AI assistants are human-like tools designed to understand natural language input in their interaction with users and offer relevant information or perform targeted actions. The current study is centred on how AI assistants are employed in e-commerce to meet the needs and preferences of users and non-users. Subsequently, the insights gathered can facilitate an understanding of the differences that exist between people from Western and Eastern cultures involved in e-commerce.

Users and non-users. For this study, users and non-users allude to individuals who interact with AI technologies as experienced and first-time customers in e-commerce businesses that have adopted AI assistants. Therefore, users are individuals who are proactive in the use of AI assistants in their regular online shopping activities (Malodia et al., 2022). These individuals are tech-savvy and tend to have a positive attitude towards AI assistants by appreciating specific features such as automation, efficiency, and personalisation. Non-users allude to individuals with limited or no experience in the use of AI technologies and have limited intentions to become active users of AI assistants in e-commerce (Lee et al., 2021). Therefore, their limited exposure to AI technologies might compromise their attitudes and intentions towards AI assistants. Understanding how users and non-users interact with AI shopping assistants is essential in developing solutions that can enhance the application of such tools to improve the customer experience and organisational performance.

Cultural background. The cultural background alludes to the shared beliefs, norms, customs, values, behaviours, and practices shared by a group of people (Straub et al., 2002). The cultural background influences how individuals from different groups perceive the world and their behaviours towards businesses and customer services (Laroche et al., 2004). Assessing how cultural backgrounds influence the adoption of AI assistants is critical in determining how factors such as language, traditions, and identities impact the effectiveness of the technology in enhancing customer satisfaction.

Western and Eastern cultures. These are broad generalisations of the cultural backgrounds emerging in the West and East global geographical settings. Hong et al. (2007) state that the categorisation of Western and Eastern cultures is a reflection of the diversity in beliefs, values, practices, and behaviours in a multicultural world. Although globalisation and increased socialisation have fostered increased cultural exchange, there are distinct characteristics associated with Western and Eastern cultures. Nunn (2012) describes Eastern cultures as the cultural traditions, values, and norms that emerge from the Asian and Middle East parts, while Western cultures allude to those experienced in Europe and North America. Focusing on Eastern and Western cultures is important to establish how AI shopping assistants deliver to a multicultural customer base.

1.6 Literature Review Overview

The literature review presents a comprehensive and critical discussion of concepts, theories, and findings from previous publications. The chapter covers the history and types of AI assistants, the roles and challenges they present, empirical research on AI assistant adoption in e-commerce, and cross-cultural perspectives on technology adoption and e-commerce. These subtopics foster an assessment of the issues of interest highlighted in the research objectives and questions. A brief history of AI assistants demonstrates a gradual development to sophisticated modern-day systems and increased diversity in their capabilities and use. Since the first chatbot, Eliza, was introduced in 1966 by Joseph Weizenbaum, there have been substantial developments in AI technologies and specialisation in their functions, including general-purpose conversational agents (e.g., Siri, Alexa), task-specific agents (e.g., customer service chatbots), menu/screen-based agents, and more sophisticated text/voice-based agents that require machine learning algorithms (Weizenbaum,1966; Aro, 2011; Guzman, 2017). AI assistants have been applied in various sectors such as banking, healthcare, tourism, and e-commerce (Siebra et al., 2018; López et al., 2017; Kalia et al., 2017; Ranoliya et al., 2017; Dahiya, 2017). They perform a variety of tasks that include customer service, interacting and offering users information, and enhancing the companies' performance (Okuda & Shoda, 2018; Milhorat et al., 2019; Kowatsch et al., 2017; Oh et al., 2017; Argal et al., 2018; Solem, 2016). Studies also highlight that AI assistants are effective in enhancing marking strategies and customer satisfaction (Chung et al., 2018; Zarouali et al., 2018). The use of AI in e-commerce is challenged by issues associated with the quality of services and user satisfaction, among other limitations emerging in the use of digital systems. Some of the major concerns emerging in empirical research concerning the use of AI assistants include user satisfaction, perceived performance, trust, and corporate reputation (Ashfaq et al., 2020; Eren, 2021). These considerations influence the users' intentions to continue using AI assistants. Perceived usefulness is a strong predictor of user satisfaction and intentions to users (Lubbe & Ngoma, 2021). Cultural factors have an impact on trust and communication, which influence the decision to engage with AI assistants (Nordheim, 2018). Therefore, cultural norms shape the attitudes individuals have towards technology as personalisation becomes an Inherent aspect of how AI assistants create competitive advantage (Kull et al., 2021; Merhi, 2021; Akour et al., 2022; Peña-García et al. (2020). The key factors that influence the behavioural intentions to use AI assistants addressed in the literature review are perceived usefulness (PU), perceived ease of use (PEU), interactive communication (ICOM), personalisation (PERS), and attitude (AT).

1.7 Research Method Overview

This section provides an overview of the research design and method used in the study. This study is an explanatory research project that aims to explain the main aspects of the research phenomenon. This study focuses on the fundamental constituents that constitute the research model. Explanatory research is vital to uncover causal relationships, particularly investigating 'what is the impact?' by exploring cause-and-effect associations among specific research phenomena (Bryman & Bell, 2015). Examining causal relationships within the primary research clusters is also a central aspect of this study. Thus, the explanatory approach and other research types, like exploratory and descriptive methods, are deemed relevant and appropriate for this investigation. The research employs a mixed-method approach, incorporating both positivism and interpretivism. Recently, mixed methods have gained popularity in social science and management studies (Liu & Huang, 2023; Alakwe, 2017) for the following reasons. Firstly, it allows researchers to draw upon the strengths of both quantitative and qualitative methods, providing a more robust understanding of the phenomenon under investigation. Combining numerical data and in-depth narratives enables a deeper exploration of complex research questions. Additionally, the mixed-method approach helps researchers triangulate findings, corroborating results from different sources, thus increasing the reliability and credibility of the study. It also allows for a more holistic perspective, considering diverse viewpoints and contexts, thereby enhancing the applicability of the research outcomes in real-world scenarios. By employing mixed methods, researchers can tackle multidimensional research questions, leading to more comprehensive and insightful conclusions that have a broader impact on theory and practice. A mixed-method approach is adopted because it provides a comprehensive understanding of this phenomenon, strengthens the validity of findings, offers practical implications, and facilitates triangulation for more robust conclusions (Dawadi et al., 2021). Meanwhile, there is limited mixed-method research on technology adoption (Fan et al., 2016).

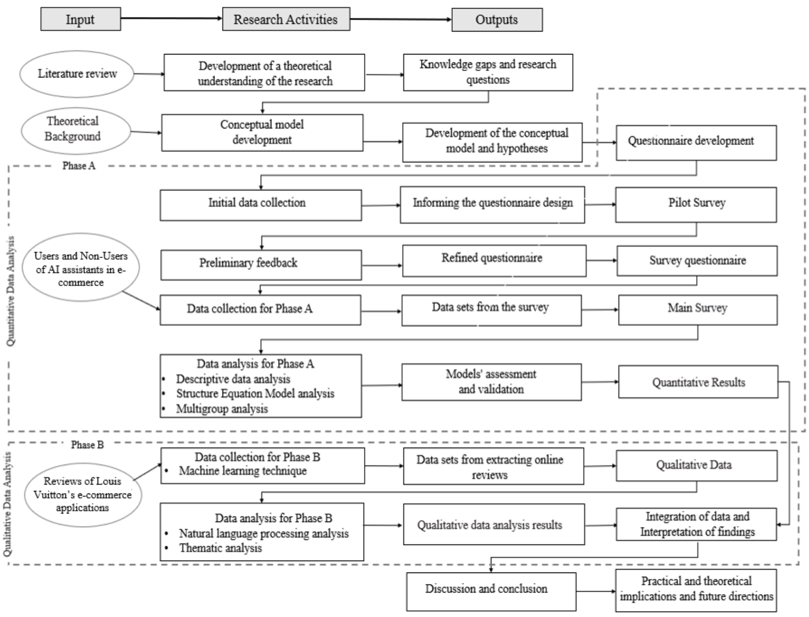

Figure 1.1. Research Design

The study began with a quantitative research method that used cross-sectional data collection to test the hypotheses. The cross-sectional analysis aims to collect data simultaneously to compare different groups of respondents (Belli, 2008). The study targets the e-commerce sector and includes participants from different cultural backgrounds. Chapter 4 provides a deep presentation of the research methodology employed in this study. The examination of the relationships between various parameters in the research model was undertaken by using the Partial Least Square Structural Equation Modelling (PLS-SEM) approach through the software SmartPLS version 4 (Ringle et al., 2014). This technique allows us to examine complex relationships between latent variables and facilitates comprehensive data analysis. The multi-group analysis (MGA) was utilised to analyse the model between two groups of the collected data. Furthermore, the qualitative research approach was employed to analyse reviews of the Louis Vuitton brand's e-commerce applications, utilising machine learning and Natural Language Processing (NLP) techniques to acquire deeper insights and construct a comprehensive understanding of the phenomenon under investigation.

1.8 Thesis Layout

This section outlines the organisational structure of this thesis, detailing the chapters and the primary contents presented within each chapter. This thesis comprises seven chapters: the introduction, literature review, research methodology, statistical analysis and outcomes, discussion, and conclusion.

Chapter 1 [Introduction] presents the thesis overview. This chapter starts with the background of the research phenomenon and identifies the research knowledge gaps. The following sections of Chapter 1 are the study's scope, the research questions, the study's objectives, the significance of this research, and the research design. This chapter culminates with an exposition of the research methodologies in this thesis and an outline of the thesis structure and its main concepts.

Chapter 2 [Literature Review] critically examines the literature related to the research topic, offering a comprehensive theoretical background for the primary research phenomenon. This chapter begins with the history of AI assistant development. After that, this chapter presents theoretical discussions on the roles of AI assistants in various domains and the factors influencing AI assistant usage in the e-commerce field. Thus, this section of the thesis expands upon the existing research factors and formulates pertinent dimensions. The study aims to construct a comprehensive conceptual framework that addresses the research questions by integrating these essential elements. The overarching goal of this chapter is to establish a solid theoretical groundwork for the integrated research phenomenon. Building on this foundation, the researcher can subsequently conceptualise the research framework, which will serve as a fundamental structure for this investigation.

Chapter 3 [Theoretical Development and Research Model] delves into the theoretical underpinnings and models that form the basis of the research model, aiming to bridge the identified knowledge gap. Building upon the comprehensive literature review conducted in Chapter 2, this chapter presents the proposed research model and its associated hypotheses. Each idea integrated into the research model is substantiated by sound justifications, aligning with the existing body of knowledge. Consequently, the output of this chapter is the development of a well-defined conceptual model, which lays the groundwork for the subsequent phases of the study.

Chapter 4 [Methodology] explains and justifies the core methodology used in this thesis, including the research approach, the research design, and the research methods. The following section of this chapter is the detailed questionnaire development, including the choice of the design creation of the questionnaire structure and measurement scales. Chapter 4 also discusses the data collection adopted in this study and ethical considerations. The chapter concludes with details of the pilot study and the primary survey with the natural language processing techniques for analysing online customer reviews.

Chapter 5 [Quantitative Data Analysis] and Chapter 6 [Qualitative Data Analysis] The data analysis approach for this study involves employing PLS-SEM testing, which is justified based on their suitability for investigating the research hypotheses. Chapter 5 presents both the measurement model assessment and the structural model assessment. Chapter 6 provides a detailed account of the results obtained through the machine learning approach. The study analyses customer reviews using NLP technologies to gain further insights. The outcomes of this NLP analysis are presented alongside the PLS-SEM results and assess whether they are supported or rejected.

Chapter 7 [Discussion and Conclusion] discusses the study outcomes for each proposed hypothesis. Chapter 7 critically discusses the research questions, investigating the relationships between the research model factors and its hypotheses. Furthermore, this chapter also revisits the research objectives and summarises the answers to the research questions, concluding the findings of this study. The researcher has presented the study's main contributions and critical managerial implications. Finally, this chapter concludes with the research limitations and recommends future directions suggesting further research opportunities.

1.9 Chapter Summary

This chapter offers a comprehensive overview of the research, encompassing the research background, problems, study scope, questions related to the research, objectives, and plan. This chapter presented the research objective and questions with their research methods. In addition, this chapter discussed the research contribution in terms of academic and practical significance. Furthermore, this thesis's research approach and design have been explained and justified. Finally, this chapter has demonstrated the overall structure of the thesis idea, covering the main points presented within each chapter. Overall, the researcher provided Chapter 1 (Introduction) to demonstrate the foundation for this thesis and based on this foundation. The next chapter will discuss the concept of conversational AI agents in e-commerce and the influencing factors that impact the usage of this AI application in terms of customers' perception and usage intention. As with any research project, a level of iteration of research stages should exist to demonstrate the consistency of the research process (Peffers et al., 2007). Therefore, this thesis attempts to narrate the study's approach from the starting point to the completion point with a reasonable level of implementation of each stage, presenting the consistency of the research process and its logical flow.

Chapter 2. Literature Review

In this section, we explore the extensive literature surrounding AI assistants, establishing the groundwork for the research model described in Chapter 3. The organisation of this chapter comprises key segments: an initiation into the realm of AI assistants, encompassing their definition, historical evolution, primary classifications, roles, and challenges; a scrutiny of past empirical investigations concerning the utilisation of AI assistants, both in a general context and specifically within the domain of e-commerce; and an examination of the factors incorporated in the current study to probe into attitudes and the intention to use AI assistants in the e-commerce area.

2.1. Introduction to AI Assistants

This section introduces AI assistants by describing the history of the development of chatbots, their main types, roles, and the challenges of applying AI assistants.

2.1.1 History and Types of AI Assistants

In the early years of 1950, many studies brought attention to the relationship between computers and humans based on communication theory. Since then, AI assistant platforms have received immense interest. An article by Alan Mathison in 1950, titled "Computing Machinery and Intelligence," offered a report based on the test of the computer's ability to think like humans, which has served as the foundation for understanding AI agents (Pinsky,1951). Table 2 presents the history of the leading chatbot development. In 1966, Joseph Weizenbaum developed the very first chatbot, Eliza. The primary reason for this development was to act as a Rogerian psychotherapist. The chatbot was developed based on the model, which performs by mirroring the prompt of the previous user. However, this model had some limitations as it failed to keep up with the flow of ongoing conversation and was also limited when recognising human-like feelings (Weizenbaum,1966). Later, in 1972, Kenneth Colby developed another chatbot named Parry at Stanford University. This chatbot responded and played a role in activating paranoid schizophrenia in a person. Depending on the embodied conversational interface, Parry was more developed and had more features than Eliza (AbuShawar & Atwell, 2015).

The Artificial Linguistic Internet Computer Entity (ALICE) was created by Richard Wallace in 1995. To determine the heuristic dialogue rules, this entity used a platform called AI Markup Language (Tabet et al., 2000). Later, in 2001, Windows created another platform called Smarter Child and integrated it into Windows Messenger to interact with people as a customised conversational interface. Apple introduced its platform in 2010, which operated as Siri, a voice assistant. Siri uses voice and text interaction modes to interact with users in their native language (Aro, 2011; Guzman, 2017). In 2015, based on Apple's model, Amazon launched its voice-based assistant, Alexa, an intelligent speaker. Inspired by this model, in 2016, Google also launched its smart speaker named Google Assistant. Samsung also adopted this trend by developing Bixby, an intelligent voice-based assistant similar to Siri in 2016.

Table 2.1. Timeline of Chatbot Development

Chatbot	Year	Interaction mode	Role
Eliza	1966	Text	Rogerian psychotherapist
Parry	1972	Text	Simulate a person with paranoid schizophrenia
ALICE	1995	Text	Practice human-like conversation
Smarter Child	2001	Text	Virtual AI Assistant
Siri	2011	Text/Voice	
Alexa	2015	Voice	
Bixby	2017	Text/Voice	
Meena	2020	Text	
Blender	2020	Text	

Google recently announced the launch of Meena, the most advanced AI assistant. Meena is an end-to-end trained neural conversational model with 2.6 billion parameters. Compared to earlier chatbots, this model facilitates more intelligent discussions (Adiwardana et al., 2020). The creation of Blender, a more sophisticated AI assistant, has been unveiled by Facebook. Compared to Meena, this assistant is anticipated to look more lifelike. However, Blender has several limitations, such as its inability to filter Reddit datasets that contain objectionable language that can affect Blender's replies (Gjurkovi & Najder, 2018).

Investigations on chatbots or AI assistants highlight the need for these technologies to facilitate human-like engagements with customers. According to Davenport et al. (2020), AI assistants can learn and respond to changes emerging among customers. Therefore, the customer experience in using AI technologies is an underlying factor that impacts their attitudes and intentions to continue using AI assistants in e-commerce. The particular characteristics emerging from the different cultures justify an exploration of how different AI assistants are adopted and implemented in e-commerce. Users can be described as individuals who routinely utilise AI assistants in e-commerce, while non-users are those with limited or no experience in the use of such technologies. According to Maedche et al. (2019), users are characterised by positive attitudes towards AI technologies because they have adequate skills and knowledge to leverage the benefits emerging from such solutions. However, non-users might be aware of the AI technologies but lack insights on how to utilise the AI assistants to enhance their shopping experience adequately. Lee et al. (2021) suggest that converting users to non-users is premised on enhancing their experience and knowledge concerning AI assistants.

The AI assistants have been divided into two types according to their functions and engagement styles. The first category hinges on discussing the various functions played by conversational agents, while the second group concentrates on technical issues, such as defining user interaction styles. Other frameworks are used in typical AI applications, such as an avatar, a conversation system, or an expert framework for more effective question processing. Figure 2.1 presents the broad type of AI assistant classification. The general-purpose conversational agent is referred to as an agent who is a personal virtual assistant and is also a multi-tasking agent. Such an agent is usually integrated into smart speakers, mobile, and desktops (Siebra et al., 2018). These applications are responsible for performing general tasks, and the users can also ask public questions. For instance, the users can ask questions about the nearest restaurant and weather, adjust the calendar, open email applications, or any other personal inquiries. Among the examples of virtual assistants that play the role of general purpose are Alexa, Siri, Cortana, Bixby, and Google Home (López et al., 2017).

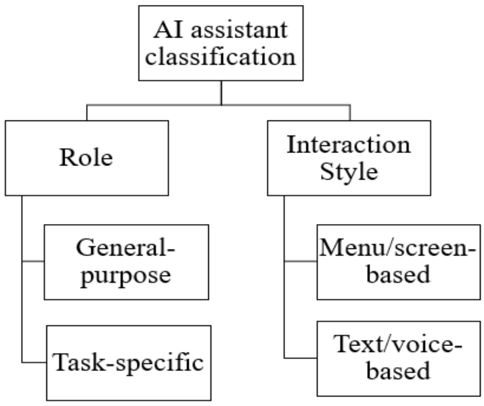

Figure 2.1. Classification of AI Assistants

The task-specific conversational agent performs tasks specifically for the users as an assistant agent for any particular domain, such as customer service, therapist, or online tutor (Kalia et al., 2017; Ranoliya et al., 2017). Such agents perform on integrated platforms like social media applications and websites. Facebook Messenger is among the popular virtual assistants used to target consumers by many firms (Pereira & Díaz, 2018). In addition, WhatsApp, Kik Messenger, Twitter, and WeChat application are also among the chatbot platforms (Xie et al., 2019; Yamaguchi et al., 2018).

The menu/screen-based conversational agent performs using predefined rules through which they can produce only a limited number of answers. The users are allowed to ask the predefined questions only, in response to which the chatbot's knowledge base generates the solution. The user interface of such a conversational agent has only end-user prompts in limited numbers. Implementing such conversational agents is very straightforward and mitigates the need for machine-learning algorithms for implementation (Dahiya, 2017). However, the menu/screen-based conversational agent is limited when answering the questions not included in the predefined list in the dataset. The benefits of such an agent are that it enhances the ease-of-use factor and navigates the conventional flow of information (Hornbæk & Hertzum, 2017). Its drawback of limited response results in the users' expressive capacity constraint.

One of the most advanced conversational agent types is the text/voice-based agent, which requires an ML algorithm to generate appropriate responses. Such conversational agent interacts directly with the end-users by allowing them to interact through unconstrained input, either through voice-by-speech, typing text, or using long sentences during the conversation. For instance, in case the user asks, "Where is the nearest saloon to my location?" the agent takes the keywords "nearest," "saloon," and "location" to determine the reply to be given to the end-user. Text/voice-based agents utilise deep learning algorithms to develop the ability to recognise and detect keywords (Khanpour et al., 2016). Such conversational agents have a dialogue manager central to the entire design because it collects the keywords from the conversational interface sent to the knowledge engine. The knowledge engine is responsible for classifying the questions and searching for appropriate responses from digital libraries (Setiaji & Wibowo, 2016).

All these data sets are available as open platforms (Serban et al., 2015). Compared to menu-based conversational agents, the text and voice-based agents allow the users to search with more text/voice-based agents for more flexibility when expressing their prompts. However, this may also lead to the misinterpretation of the prompt, which has a high chance of returning with a negative response to the user, leading to a poor experience. The AI assistants have applications in various domains like finance, travel, education, E-commerce, banking, and healthcare. The following section discusses these applications.

2.1.2 Roles and Challenges of AI Assistants

Conversational systems have applications in several sectors, including healthcare, business, education, travel, and finance. Table 2 summarises the AI assistant's role in various domains. The conversational application aids learning by utilising the appropriate dialogue scenario design in the educational sector, resulting in a less complex knowledge structure. Previous studies have covered using AI assistants in the classroom and for student learning. For instance, Sánchez-Daz et al. (2018) created a formal technique to support the university-level course with a virtual assistant-based tutor. Clarizia et al. (2018) presented an ontology-based virtual assistant in education. Using NLP techniques, this virtual assistant finds the keywords to give pupils the correct answers. To assist teachers and students with learning tasks like spotting spelling or grammar errors, reviewing homework, assigning projects, etc., virtual AI platforms are helpful. In their research, Kerlyl et al. (2006) suggested that a negotiated open learner model would be more advantageous for creating conversational agents and putting in place intelligent tutoring systems to assist students in their learning process. The researchers proposed that introducing a virtual assistant that has the ability not only to negotiate but also to incorporate small talk can have a beneficial impact as it serves the purpose of enjoyment in engagement and interaction with the chatbot, which has the capability of improving the students' experience of learning. Hien et al. (2018) developed a virtual assistant to provide services for academic staff and students. Such assistants have high user intent identification along with context extraction accuracy. These virtual assistants show promising results regarding context information and intent identification, i.e., if the context information extraction score is high, it indicates that the virtual assistant can provide the correct answers.

AI virtual assistants work as customer service agents for large-scale inquiries for clients in the financial sector, providing information about services like home loans, car loans, and FAQs for those customers who own car loan contracts. Okuda and Shoda (2018), when examining the features of the AI virtual assistant implemented in Sony Bank, found that it has developed a function of the user stream, which visualises the number of users that have passed through different contexts. Visualising the user stream function is essential as it helps gather information about the script locations that require amendments regarding the detailed response for developing the AI virtual assistant's conversation suitability. Altinok (2018) put forth a framework for the banking and finance industry. The framework was created for German language banking using the financial AI assistant to improve the dialogue between consumers and the virtual assistant. Although this architecture showed promising results, work is currently being done to introduce success metrics and assess the dialogue manager module. Duijst (2017) presented an AI virtual assistant for the banks, which serves the purpose of investigating the factors of personalisation, which can be beneficial in improving the user experience of chatbots. The scholar also demonstrated no significant impact of personalisation on the user experience of chatbots when it comes to the finance industry.

In the banking industry, conversational agents assist end users in various ways. These responsibilities may include paying bills, responding to user account-related questions, processing credit card payments, carrying out transactions, and setting up meetings. Milhorat et al. (2019) study looked into the impact of AI virtual assistants in banking. The researchers investigated it by creating a dialogue management system that can respond adequately and reduce the incidence of any generic fallback. Two hundred twenty-six users participated in the study, of whom 187 gave accurate answers, and 39 gave fallback utterances highlighting the coherent statement response component.

Conversational agents are also used in the healthcare sector to inform patients and caretakers about their medical issues (Kowatsch et al., 2017; Oh et al., 2017). Huang et al. (2018) created a virtual AI healthcare assistant using user data. This virtual assistant can advise diabetic patients on what foods to eat and stay away from as part of their diet. AI in medicine has potential benefits since it enables personalised information delivery to individuals in various practical contexts (Kocaballi et al., 2019a). However, additional research is still required to guarantee the security of the patient (Laranjo et al., 2018). Recent studies have demonstrated the potent influence of AI technologies in providing knowledge for averting the COVID-19 pandemic (Miner et al., 2020). This is made feasible by creating an AI-based chatbot that, in addition to helping to battle COVID-19, also helped strengthen the influence of healthcare management (Martin et al., 2020). An example is the creation of a web-based AI virtual assistant was suggested by Espinoza et al. (2020) as a solution to the COVID-19 pandemic, which is advantageous in filtering and rerouting consumers via the links dispersed over many channels, such as email, social media, and text messages. The screening questions are handled, and answers are generated to direct people to the best healthcare options.

The AI virtual assistant is vital in tourism and travel, providing services via conversation-like interactions. The AI assistants are helpful in how consumers book their trips, discover new experiences, plan their vacations, and make reservations at their preferred hotels. Argal et al. (2018) developed an AI assistant for improving user-machine interaction in the travel industry. This assistant is helpful as it collects the user data and preferences for generating the desirable results and recommending accordingly to the user, along with providing accurate information about their travel. Sano et al. (2018) also implemented a tourism AI virtual assistant based on the agglomerative nesting algorithm and hierarchical cluster analysis, which balances the time and quality of tours on different tourism sites.

Their primary objectives in terms of business are to increase sales and improve client engagement and services (Solem, 2016). Combining AI technology makes it simple to achieve these objectives (Brynjolfsson & McAfee, 2017). Researchers claim that Facebook chatbot applications have a significant impact on brand engagement. According to studies (Leong et al., 2018; Shareef et al., 2018), user-generated content and consumer participation on Facebook have positively impacted consumer engagement with brands. According to Lee and Ko's (2019) research, AI virtual assistants favour branding relationships, creativity, hedonic value, and customising functionality. Bhawiyuga et al. (2017) created an artificial intelligence (AI) assistant system to engage with consumers using the Telegram service and automatically generate responses to customer-to-seller inquiries within 5 seconds.

AI virtual assistant plays many vital roles in the e-commerce domain, including asking for customer feedback, sending messages for advertisement, collecting data regarding the customer's preferences, and improving the consumer's engagement with the brand. Two studies support the opinion that chatbots play a vital role in enhancing the marketing strategies of brands and leading to customer satisfaction (Chung et al., 2018; Zarouali et al., 2018). However, there is still a need to investigate the practical impact of using AI virtual assistants in e-commerce as a marketing channel and consider all the minor details, like the customer's perception. AI assistant plays the role of enhancing the online shopping experience of the customers as it provides relevant recommendations and information for the customers online. This improves the browsing of the customers' products, as finding the preferred outcome among the massive variety of products on the website can be much more time-consuming and challenging. For example, a website-based chatbot developed by Gupta et al. (2015) works as an online automated assistant by suggesting products that match customers' preferences.

Today, almost all the existing brands depend upon social media sites to improve customer-brand relationships and distribute information to customers. However, there is a limitation to it as social media sites contain content in massive amounts, and a poorly generated post can lead to increasing difficulty for customers in finding information about the brand quickly. In such a case, a conversational AI agent is influential as it helps the customers engage with the brand and find their information. However, there are still many challenges when it comes to designing, making conversations, and evaluating the satisfactory experience for the customers (Kocaballi et al., 2019b). Despite this, AI virtual assistant shows improved results regarding customer service technologies and marketing channels. The AI virtual assistants already existing in the marketing channels have several cons, including the need to support third-party integration, poor interactive user interface, and multilingualism. They cannot detect customer emotions (Nuruzzaman & Hussain, 2018).

Some recent studies have investigated and sided with the effectiveness of using AI virtual assistants for brand strategies and online marketing (Chung et al., 2018; Zarouali et al., 2018). Also, much research is being carried out to determine the potential of online AI assistants when working as an online marketing tool. These studies also focus on the enhancement of customer engagement using conversational agents. Further, in the future, these researchers might shift their focus to investigating the customer's attitude toward the involvement of the conversational agents in marketing along with the factors that influence the user's satisfaction with the conversational agents. Currently, consumer experience quality assessment is a trendy topic under the HCI discipline (Kocaballi et al., 2019b). Further, there is an area of improvement in the design of the conversational application depending on the feedback of the customer's experience. Also, certain areas of the conversational agents that need improvement can be found through the customer's perspective to enhance the conversation's outcomes and capabilities.

2.2 Empirical Research on AI Assistant Adoption in E-commerce

This section elaborates on studies investigating AI assistant use in e-commerce to provide a comparative analysis of related work and results. Identified pertinent studies through electronic databases, including Scopus, Web of Science, and Science Direct (Ashfaq et al., 2020; Kasilingam, 2020; Pillai et al., 2020; Zarouali et al., 2018). To gain comprehensive insights into the topic, the subsequent sections encompass research on the utilisation of a conversational AI agent in e-commerce domains. The objective was to establish a suitable theoretical and empirical foundation for constructing the research model in this study and pinpoint the most relevant factors for investigating attitudes and behavioural intentions to use AI assistants in e-commerce.

Previous studies show that user satisfaction is inherent in developing the intention to use AI assistants. Findings by Ashfaq et al. (2020) show that user satisfaction with chatbot e-services was a key determinant and predictor of continuous intention to use, highlighting the need to improve the quality of services and information offered to consumers. The authors recommended the integration of human service employees to enhance user satisfaction with digital services. Aligned with these findings, Luo et al. (2019) found that in cases where chatbot identity was disclosed to the customers before a conversation, there was a 79.7% decrease in purchase rates, which shows that customers value human interactions compared to chatbots. According to Eren (2021), customer satisfaction in using chatbots in the banking sector is influenced by perceived performance, trust, and corporate reputation. Insights from Lubbe and Ngoma (2021) show that perceived usefulness (PU) is the strongest predictor of satisfaction among customers using chatbots. Kim and Chang (2020) found that the chatbot service quality does not affect user satisfaction and reliability. Further insights from the authors show that the achievements made in satisfaction, reliability, and immersion when using chatbots influence the customers' reuse intentions.

The perceptions users have concerning chatbots influence the decisions made by an individual. According to Araujo (2018), chatbots that use human-like language or names effectively develop the perception that the systems could satisfy user needs like human workers. However, Go and Sundar (2019) stress that although chatbots increasingly replace humans in online customer services, their interactions are often machine-like. According to Sheehan et al. (2020), anthropomorphic chatbots can lead to enhanced customer satisfaction because they can meet their social desires for human transactions.

The customers' intention to use AI assistants is influenced by access to information that can enhance their understanding and perceptions of the technology. According to Rese et al. (2020), the intention to use chatbots is influenced by the customer's insight, including utilitarian aspects such as the authenticity of conversation between the users and the chatbot and the perceived usefulness established by individuals. The researcher adds that the intention and frequency of use can be impacted by the customers' concerns about privacy when using the system. Van den Broek et al. (2019) show that the perceived helpfulness and usefulness of the chatbot influence the perceived intrusiveness of chatbot advertising and patronage intentions. This implies that individuals with adequate access to information, including the chatbot capabilities, can make informed decisions on its use. Table 2.2 synthesises the key factors affecting the intention to adopt AI assistants.

Previous studies show that the increased application of chatbots in e-commerce has contributed to its acceptance with improved customer experience. Moriuchi et al. (2021) show that users develop a positive attitude toward using chatbots, leading to increased engagement, while higher user satisfaction enhances the revisit intention on the online platforms. Sfenrianto and Vivensius (2020) show a positive correlation between customer experience and an array of factors, including information quality, system quality, service quality, e-trust, e-satisfaction, and e-loyalty. These findings are supported by insights from Pillai et al. (2020), who show that the innovativeness and optimism among consumers influence the perceived ease and usefulness of AI-powered systems in the retail sector. Furthermore, Pillai et al. (2020) established that insecurity in using AI negatively impacts the perceived usefulness, which, when integrated with perceived ease of use, enjoyment, customisation, and interactivity, are predictors of the customers' intention to shop in AI-powered automated stores.

Studies demonstrate that anthropomorphism in using chatbots is a critical consideration in developing brand engagement and purchase decisions. Research by Han (2021) shows that human-like features in online shopping and customer service assistants improve customer engagement and the subsequent intention to purchase. In the same context, Kull et al. (2021) show that the increased use of chatbots in customer services requires effective messaging tailored to individual visitors, enhancing customer-brand connections.

Although chatbots have enhanced customer service and support, various considerations are critical in their effective implementation. Nordheim (2018) shows that the effective use of chatbots requires developing trust among users. Additional considerations include chatbot-related factors such as expertise, absence of marketing, fast response, and anthropomorphism, which are characteristics of an effective chatbot. The researcher also established that access to human operators enhanced the use of chatbots because it increased trust in the technology. Mimoun and Poncin (2015) demonstrate that using embodied conversational agents (ECA) requires improving the users' perceptions of shopping value to enhance their experience. According to Selamat and Windasari (2021), the strategic objective in adopting chatbots is to create a positive customer experience, especially when implemented in SMEs. This can be achieved by developing responsive systems, triggering customer actions, and fostering humanised conversations and personalisation. Li et al. (2020) found that AI customer services enhance users' online shopping experience. However, there are challenges in fostering a seamless bridge between technology and human agents. The use of AI systems is also influenced by customer attitudes that vary among customers with different characteristics. Therefore, businesses must foster a strategic and orderly approach to using human agents versus AI chatbots. Rhee and Choi (2020) suggest that customers can be more inspired to use chatbots with voice-based conversational agents that enhance personalisation. In this light, the personalisation and social aspects of the chatbots enhance the positive attitudes among customers promoting their application in shopping.

Table 2.2. Key factors affecting the adoption of AI assistants

Key Factor	Study
Perceived Usefulness, Perceived Ease of Use, Perceived Anthropomorphism, Perceived Intelligence, Perceived Animacy	Balakrishnan and Dwivedi, 2024
Perceived Competence, Trustworthiness	Choudhury et al., 2024
Personalisation, Conversational Tone, Autonomy, Responsiveness	Guo and Luo, 2023
Usefulness, Ease of Use, Anthropomorphism, Sociability, Enjoyment, Privacy, Trust	Singh et al., 2024
Information Quality, Service Quality, Perceived Enjoyment, Perceived Usefulness, Perceived Ease of Use	Ashfaq et al., 2020
Human-like Cues, Framing, Anthropomorphism	Araujo et al., 2018
Responsive Features, Social Conversations, Personalized Recommendations	Selamat et al., 2021
Authenticity of Conversation, Perceived Usefulness, Perceived Enjoyment	Rese et al., 2020
Initial Message, Brand Self-distance, Miscommunication, Anthropomorphism	Kull et al., 2021
Message Interactivity, Social Role, Involvement	Go and Sundar, 2019. Rhee and Choi, 2020
Information Quality, System Quality, Service Quality, e-Trust, e-Satisfaction, e-Loyalty	Sfenrianto and Vivensius, 2020
Expertise, Anthropomorphism, Response Time	Nordheim, 2018

Previous studies employed different methodologies and explored factors associated with applying AI assistants (Balakrishnan & Dwivedi, 2024; Choudhury et al., 2024; Guo & Luo, 2023). The studies also provided contradictory evidence on factors influencing AI assistant use. Table 2.3 provides a summary of recent empirical studies on AI assistant use. In contrast, certain aspects of technology adoption models have not been examined within the realm of AI assistant utilisation in e-commerce (Singh et al., 2024; Araujo et al., 2018; Selamat et al., 2021). Furthermore, previous research on AI assistants has predominantly focused on Western countries or specific cultural contexts (Istiqomah & Alfansi, 2024; Kull et al., 2021; Sheehan et al., 2020; Mimoun & Poncin, 2015), making their findings potentially less applicable to individuals in different contexts due to cultural and other variations. Notably, entire regions have been excluded from prior investigations, or studies have predominantly explored countries diverging from the Eastern context and culture (Li et al., 2020; Pillai et al., 2020; Kull et al., 2021). Therefore, the current knowledge gaps are:

- Not enough study on how people adopt technology: Researchers haven't closely examined all aspects of how individuals decide to use AI assistants in e-commerce contexts.

-Some countries and cultures are excluded: Most studies have focused on AI assistants in Western countries or specific cultures. This might mean their findings don't fit well for users or potential users in other places.

-Looking at how different users use technology: More research is needed to compare how users and non-users perceive AI assistants in online shopping.

Thus, the aim of this research is to address these gaps by examining distinctions between Western and Eastern consumers. The following sections elaborate on the cultural differences and cross-cultural perspectives on technology adoption and e-commerce.

Table 2.3. Summary of Recent Empirical Studies on AI Assistant Use

Study	Purpose	Method	Findings	Limitations
Balakrishnan and Dwivedi, 2024	Explore factors influencing users' attitudes and purchase intentions towards digital assistants.	TAM model and SEM for data analysis. 440 participants in India with prior experience using digital assistants	Perceived ease of use, perceived usefulness, perceived anthropomorphism, perceived intelligence, and perceived animacy all had a positive impact on users' attitudes towards digital assistants. Users' positive attitudes also increased their purchase intentions.	Non-random sampling and focusing only on Indian users.
Choudhury et al., 2024	Investigate how users perceive and use ChatGPT in healthcare decision-making.	An online survey was conducted with adults in the United States who used ChatGPT. 607 respondents.	Perceived competence and trustworthiness of ChatGPT are crucial in healthcare. Security and persuasiveness are not related to healthcare contexts.	The data was collected only from U.S. adults, and only a small number of them used ChatGPT. Non-random sampling and reliance on self-reported data.
Guo and Luo, 2023	Examine factors influencing purchase intention in intelligent personal assistants.	Offline survey. 428 valid questionnaires were collected.	Personalisation, conversational tone, autonomy, and responsiveness positively impact informational and emotional support. Informational and emotional support positively affects purchase intention.	Focused only on Generation Z consumers in China.
Singh et al., 2024	Examine acceptance of Online Shopping Assistants in e-commerce	Used the TAM Model. 272 participants completed the online survey.	Usefulness, ease of use, anthropomorphism, sociability, enjoyment, privacy, and trust significantly impact the acceptance of online shopping assistants.	Focused on accepting assistants in low-risk consumer products.
Ashfaq et al., 2020	Drivers of users' satisfaction and continuance intention toward chatbot-based customer service.	Model: Expectation-confirmation model, information system success, and TAM Country: United States Sample: 370 actual users from Amazon's Mechanical Turk.	Information quality and service quality positively influence satisfaction. Perceived enjoyment, perceived usefulness, and perceived ease of use are significant predictors of continuance intention.	Did not include marketing and communication factors. Limited sample.
Araujo et al., 2018	How human-like cues such as language style and name and the framing used to introduce the chatbot to the customers influences their perceptions of the social aspects, mindful and mindless anthropomorphism	Model: Experimental design Country: Netherlands Sample: 207 Facebook users	The study established that a human-like agent was associated with higher levels of mindless and mindful anthropomorphism than a machine-like agent.	The study uses a small sample that is limited to Facebook users.

Selamat et al., 2021	Determining the chatbot features and elements that are appropriate based on customers' characteristics	Model: Anthropomorphism, perceived enjoyment, perceived ease of use, perceived usefulness, Country: Sample: 315 customers	The critical considerations for chatbots are responsive features, simple steps to trigger customer actions, social conversations, and personalised recommendations.	The study lacks to consider the diversity among customers and their requirements to meet customer needs in different industries.
Rese et al., 2020	Contrasting the technology acceptance model (TAM) with the uses and gratifications theories in determining the acceptance of the text-based "Emma" chatbot among target consumers	Model: TAM and uses and gratifications theories Country: Germany Sample: 205 German Millennial	The acceptance of the chatbot was influenced by utilitarian factors such as the authenticity of the conversation and perceived usefulness, as well as hedonic aspects like perceived enjoyment. There was an insignificant deviation between the models.	The research used a small sample that reflects the German setting.
Van den Broeck et al., 2019	Predicting perceived intrusiveness of chatbot advertising based on the perceived helpfulness and usefulness and subsequent influence on patronage intentions	Model: Multiple linear regression Country: Belgium/Netherlands Sample: 245 Facebook users between 18 and 35 years	The perceived intrusiveness of chatbot advertising relies on the users' perceived helpfulness and usefulness.	The study used a small research sample and was limited to Facebook users.
Kull et al., 2021	To determine a strategic approach for managers to tailor the initial message of the chatbot to enhance consumer-brand connections and engagement	Model: Experimental tests Country: United States Sample: 82 university students	Chatbots start conversations using a warm message that increases engagement, and the message can be mediated by brand self-distance that allows individuals to feel closer to the brand.	The small sample and geographical limitations show that the findings are not universal.
Sheehan et al., 2020	Relationship between miscommunication and adoption of customer service chatbots	Model: None Country: United States Sample: 200 Americans from Amazon's Mechanical Turk (MTurk)	Lack of effectiveness in addressing miscommunication errors reduces anthropomorphism and adoption intent	The study uses a small sample and focuses on the American context
Go and Sundar, 2019	To establish what can be done to humanised chatbots	Model: Factorial experiment Country: United States Sample: 141 e-commerce customers who interacted with chatbots	There is a high level of message interactivity that compensates for the impersonal nature of a chatbot that is low on anthropomorphic visual cues	The study relies on a small population sample
Rhee and Choi, 2020	Determining the persuasion mechanism used in product recommendations made by a voice-based conversational agent and the impact personalisation of content has on consumers' attitudes in voice shopping.	Model: Dual modes of information-processing models Country: South Korea Sample: 122	There is a significant interaction effect for the social role and involvement when using voice-based conversational agents.	The study relied on a small sample.
Lubbe and Ngoma, 2021	How perceived ease of use, perceived playfulness, and perceived usefulness of chatbots influence	Model: TAM, exploratory factor analysis and multiple regression analysis Country: South Africa	Perceived ease of use, perceived playfulness and perceived usefulness significantly and positively impact	The sample focused only focused on millennials in South Africa.

	customer experience and satisfaction in emerging markets	Sample: 333 South African millennials	customer experience and satisfaction when using chatbots.	
Moriuchi et al., 2021	The consumers' attitude and engagement with chatbots in customer service in a retail environment	Model: The theory of conversation and partially observed Markov decision process Country: United States Sample: 68 respondents from a private university	A positive attitude towards using technology leads to increased engagement and high satisfaction, increasing the revisit intention.	The study uses a small sample of millennial consumers and lacks adequate insights into the role of technology engagement using different technological solutions in various types of businesses, such as business-to-business
Sfenrianto and, Vivensius 2020	Determining the factors that affect customer experience when using e-commerce services that have a chatbot that helps individuals to do transactions	Model: IS Success Model Country: Indonesia Sample: 385 individuals who engaged in active transactions in e-commerce platforms that have implemented chatbot technology	The correlation between Information quality, system quality, service quality, e-trust, e-satisfaction, and e-loyalty influences customer experience in e-commerce that uses chatbots	The study uses a small sample from Indonesia and lacks to address diverse e-commerce services such as banking.
Istiqomah and Alfansi, 2024	Expolre the role of attitude towards the use of AI-enhanced fashion e-commerce	270 respondents who made at least two fashion purchases online.	Perceived benefit and perceived ease of use positively influence actual use. Perceived benefit and perceived ease of use positively affect attitude towards use.	Focused on consumers in Indonesia's fashion e-commerce sector.
Han, 2021	Assessing the impact of anthropomorphism on consumers' perceptions concerning mobile messenger chatbots and its impact on behavioural decision-making	Model: None Country: United States Sample: 170 university students with mobile phones	Anthropomorphism is critical in shaping the consumers' intentions to purchase from businesses using chatbots	The study uses a small sample based in New York.
Eren, (2021).	The impact of perceived trust in chatbots and reputation on customer satisfaction	Model: None Country: Turkey Sample: 240 customers who transacted using a chatbot	Customer satisfaction in chatbots is significantly affected by perceived performance, trust, and corporate reputation.	Limited research samples from Turkey.
Mimoun and Poncin 2015	Determining how the use of ECA can improve the users' perceptions concerning shopping value and the consequences for their purchase intentions and satisfaction with the website	Model: Embodied conversational agents (ECA) usage consequences: playfulness, decision quality, and social presence Country: France Sample: 576 French consumers	It is imperative to account for utilitarian and hedonic features to understand ECA outputs in e-commerce sites.	The findings of the study are applicable in the French context.
Nordheim 2018	Determining factors that affect trust in chatbots	Model: Framework on trust in websites Country: Norway Sample: 154 users of customer service chatbots	The users' trust is affected by expertise, anthropomorphism, low risk and not trust relevant/no trust, fast response, absence of marketing, brand, and access to a human operator.	The limitations emerge in using questionnaires in data collection, which could have introduced bias and interpretation inaccuracies.

Kim and Chang, 2020	The impact of chatbot service quality on user satisfaction and reliability	Model: IS success and service quality model Country: Korea Sample: 218 users in their teens and 70s who had experience using chatbot services	User satisfaction is not affected by the chatbot service quality. Reuse intention is influenced by satisfaction, reliability, and immersion in chatbot services.	The study involved a small sample, and the findings are limited to the Korean context.

2.3 Cross-Cultural Perspectives on Technology Adoption and E-commerce

Culture plays a critical role in the adoption of new technologies. Various conceptualisations and perceptions demonstrate how cultural factors impact the adoption of new technologies in the e-commerce context. The cultural background influences the behavioural intentions that emerge among a group of people concerning the use of particular technologies (Faqih, 2016). The culture shared among the target customer base can help determine how individuals make decisions concerning the use of particular technologies (Yi et al., 2016). Understanding culture sets the premise for designing AI solutions that can adequately meet the specific needs and preferences of different customers. According to Lin and Hsieh (2007), the impact culture has on behavioural intentions reflects how technologies that satisfy individuals from a particular group can be designed, adopted, and implemented to benefit individuals and the companies involved.

According to Merhi (2021), the variations that emerge among cultures and societies in using e-commerce can be attributed to people's cultural values, beliefs, norms, and attitudes toward new technologies. For instance, Akour et al. (2022) established that people's trust in e-commerce varies among people from different cultures, which impacts adoption and widespread usage. In this context, some cultures value face-to-face interactions and human relationships with companies, which limits their uptake of e-commerce services. Drawing from Hofstede's cultural dimensions, Faqih (2022) show that the power distance dimension affects the trust and confidence individuals from some cultures have towards online transactions. Filieri and Mariani (2021) argue that cultures characterised by low power distance are more to explore innovations and smaller e-commerce platforms, while high-power distance cultures are more attracted to established brands and online platforms. Mou et al. (2020) argue that individuals from cultures with high uncertainty avoidance are characterised by risk-averse behaviours in using new technologies, which implies that e-commerce is more likely to proliferate in cultures that demonstrate low uncertainty avoidance. According to Li and Wang (2023), adopting e-commerce among different cultures is subject to people's preferred communication styles. The study suggests that some cultures are interested in services that entail explicit and direct communication, such as straightforward descriptions of products and transparency in transactions. In contrast, in some cultures, such considerations might not impede the adoption of e-commerce. Sobti (2019) found that payment methods diver across cultures, considering that in some countries, the available options and infrastructure facilitate seamless electronic transactions such as credit cards and mobile payments, while in others, there is a high preference for using cash.

An emphasis on communalism characterises Eastern cultures through the interconnectedness that exists among the people. In the East religions that include Buddhism, Hinduism, and Islam have a significant influence on values and practices (Mokhlis, 2009). Western cultures embrace individualism that is characterised by autonomy and self-expression (Cherrier, 2007). Therefore, cultural backgrounds influence how individuals perceive technology as a community and in their individual contexts. Cultural differences influence the attitudes that exist among individuals in the use of e-commerce. Peña-García et al. (2020) suggest that cultural norms and values impact the attitudes that build up toward using technology, considering that some societies value the stability associated with their traditions. In contrast, others have become more open and accept innovation and technological advancements. A study in Taiwan by Daowd et al. (2021) established that local languages were a critical consideration among online consumers when adopting online shopping platforms. Therefore, e-commerce applications developed in the local language were more likely to be accepted and used by consumers due to the enhanced ability to understand information and communicate with the service or product providers (Elsholz et al., 2019). Chawla and Kumar (2022) noted that e-commerce platforms that demonstrate high levels of information security are more likely to be embraced in cultures where trust is inherent in the relationship between the companies and their consumers. The attitude towards e-commerce is also shaped by social influences whereby word-of-mouth and fear of missing out (FOMO) play a critical role in how individuals engage online (Kamalia et al., 2022; Rana & Arora, 2022).

Cross-cultural investigations addressing the use of AI assistants are critical to understanding how consumers from different cultural backgrounds interact with the technologies and how such interactions are influenced by their characteristic values, preferences, and norms. Subsequently, the insights gathered can help technology develop to adapt the business processes, products, or services in alignment with the expectations and needs of the target markets. According to Nam et al. (2021), personalising online services is challenging because it requires an in-depth understanding of the target consumers to enhance their experience and create a competitive advantage. Chi et al. (2023) recommended that in a diverse global virtual market, it is critical to understand cultural nuances to ensure that the services offered resonate with users' beliefs and values. These insights reflect sentiments expressed by Tsai et al. (2021), who highlight that ethical considerations should be embedded in using AI assistants to ensure an enhanced experience from virtual customer care agents similar to what individuals would experience when dealing with a human representative. Insights from Skjerve et al. (2023) show that cross-cultural perspectives in developing AI assistants are necessary in the health sector to address language barriers and improve communicative processes in the services offered. Such considerations can enhance customer satisfaction and create opportunities for expansion in new markets.

The potential implications of cultural differences in the acceptance of AI assistants among online consumers are reflected in individuals' trust and confidence that the technologies can meet their needs and expectations compared to human representatives. Furthermore, Shneiderman (2020) stressed that the successful application of AI technologies in commercial services must demonstrate high reliability, security, and privacy and meet customer needs and expectations. AI developers must offer attractive benefits in the context of personalisation in terms of language, user interface, and design. Aligning such features with the cultural preferences of the target market can increase adoption and value for the companies and customers. Additionally, the relevance of culture in e-commerce shows that the AI assistants have to express social and emotional intelligence to establish interpersonal relationships and emotional connections reflected where people are involved in the communication processes (Drigas et al., 2023). Therefore, cultural sensitivity is at the heart of developing AI assistants that can adequately engage with people from diverse backgrounds, considering that consumer attitudes, perceptions, and communication between Western and Eastern cultures vary significantly.

Despite the growing body of literature on how cross-cultural differences impact the use of AI assistants in e-commerce, further research is needed to address the trends and changes in the use of these technologies over time in different cultures. There is also a need to compare Eastern and Western cultures in the context of cultural dimensions such as power distance to highlight how cultural nuances impact the adoption of AI assistants. Further research can address multilingual AI assistants' impact on e-commerce and establish if cultural sensitivity and ethical considerations are integrated when using different languages to engage with a diverse customer base. The subsequent sections provide detailed insights into the factors employed in the current study to examine the intention to use AI assistants among consumers in both Western and Eastern contexts.

2.4 Factors Impact Behavioural Intention to Use AI Assistants

In the preceding sections, elements subjected to both theoretical and empirical analysis were identified, shedding light on how consumers make decisions regarding the adoption of innovative technologies, such as AI assistants, across various contexts and domains. Further exploration of previous research on the use of AI assistants and related areas is carried out below to discern and delve into the most pertinent factors for examining the current research topic.

2.4.1 Perceived Usefulness (PU)

Perceived usefulness is a critical aspect of technology acceptance and adoption. It highlights the extent to which individuals believe that a particular technology can help them by improving their performance, productivity, and effectiveness in meeting specific objectives or completing a task (Tahar et al., 2020). From this perspective, PU in AI assistants can be described as the perception that technology can add value or benefit the user engaged in e-commerce. This implies that PU is a subjective evaluation by the user shaped by the experiences and expectations concerning the capabilities of the AI assistants. De Kervenoael et al. (2020) suggest that the use of technology among people is influenced by its relevance to their tasks. Therefore, the perception that AI assistants can support or enhance the user's experience increases their likelihood of adopting it. McLean et al. (2021) show that PU is linked to task efficiency, and individuals are more likely to use AI assistants if they believe it can simplify complex issues. In this context, if individuals feel that the AI assistant leads to substantial improvements compared to alternatives such as human actors, then its PU increases. Further insights from Shiau et al. (2020) show that PU improves the intention to use a technology where there is a clear understanding of the advantages and benefits it brings in performing a particular task. Learning and understanding the features and functionalities of the AI assistant is critical in how individuals consider it a helpful tool. Despite this, there is a lack of adequate insights addressing how the AI assistant's PU contributes to the increased adoption of e-commerce among consumers from different cultural backgrounds. Addressing the PU concept from this perspective can enhance how developers and e-commerce companies implement AI assistants that add value to how consumers utilise online platforms.

2.4.2 Perceived Ease of Use (PEU)

The PEU alludes to the subjective assessment of individuals using or learning a particular technology (Tahar et al., 2020). From this perspective, PEU, in the context of AI assistants, highlights the users' feelings concerning the overall user-friendliness of the features and functions of the technology. According to Sarkar et al. (2020), the PEU is influenced by the user interface design that facilitates interaction between the user and the system. Alves et al. (2020) suggest that PEU can be enhanced when the user interface is intuitive, visually appealing, and informative for more efficient navigation and user interaction. Selamat and Windasari (2021) note that PEU influenced online platform use because it determined how quickly users learned and effectively used the features, including AI technologies. Suggestively, a complex and challenging system for users to learn can discourage the continued use of the technology. Yen (2023) argued that a high PEU among users fosters a seamless and coherent interaction that is critical in meeting customer satisfaction in the facilitation offered by online platforms. Focus on improving PEU for users engaging with AI assistants can enhance their ability to perform tasks efficiently and limit the frustrations associated with using such features in e-commerce (Gümüş & Çark, 2021). Al-Adwan et al. (2023) recommend implementing new features on online platforms, such as AI customer services, which should be associated with facilitation in training and provision of adequate information to enhance PEU. Harrigan et al. (2023) established that PEU in using online technologies can be influenced by social factors such as peers' recommendations and the users' technological capabilities. However, there is a research gap in how PEU shapes the decision to use AI assistants in e-commerce, considering the technological disparity and the differences in digital skills among people from different cultural settings.

2.4.3 Interactive Communication (ICOM)

According to Billion and Van den Abeele (2007), ICOM is the communicative process that entails the active participation of two or more parties in a dynamic and bidirectional exchange of information, including real-time responses and feedback. ICOM can be experienced through various channels, such as face-to-face interactions, phone calls, video conferencing, social media, and chatting on online platforms. Kim et al. (2023) demonstrated that the effectiveness of chatbots in online platforms can be attributed to the real-time communication between the system that represents the company and its users. This interaction facilitates timely responses and access to customer needs information. Therefore, customers are more attracted to systems where ICOM makes them key stakeholders in determining the quality of services offered in a personalised context (Choi et al., 2020). Dwivedi et al. (2022) highlighted that ICOM allows active engagement of all parties, which creates an opportunity for developing inclusive services where all users' opinions, concerns, and interests are considered in the services offered. Cheng and Jiang (2022) found that the immediate feedback from chatbots contributed to the customers' intention to use online services when seeking information about the company offerings and positively impacted their decision to purchase. These insights show that ICOM promotes positive attitudes towards AI technologies, companies, products, and services. Furthermore, an effective ICOM gives customers an enhanced understanding because they can seek clarification and additional information to make informed purchase decisions. Schanke et al. (2021) found that the increased use of chatbots compromised customer satisfaction with the company because it eliminates the human touch, which is critical in developing healthy customer relationships. The research gap in this context is that despite ICOM being a valuable form of communication, there is a need to establish the various underlying factors that the AI assistants must meet to enhance the relationship with the e-commerce companies to achieve better outcomes than in interactions with human representatives.

2.4.4 Personalisation (PERS)

Hsu et al. (2021) highlight that each consumer is unique, making it imperative that companies consider tailoring products and services to meet their needs and characteristics. Chandra et al. (2022) described personalisation as providing the right services or products at the right time, in the right place, and to the right person. In the e-commerce context, Selamat et al. (2021) suggest that personalisation is premised on accessing, analysing, and acting on large volumes of consumer data that might be historical or real-time and using it to understand and predict customer behaviours with the intent of offering services or products they can relate with. A study in the banking sector by Kaaniche et al. (2020) found that customers are substantially attracted to online banking providers that demonstrate enhanced capacity to offer quality, secure, and personalised services. Saniuk et al. (2020) supported these findings by stating that modern consumers expect personalisation in online services. Companies with online operations have responded to these expectations by implementing sophisticated technological solutions such as AI and ML technologies, enabling them to respond to each customer's needs adequately and effectively. These developments are aligned with the increased focus on the data-driven approach in decision-making that entails using customer data from the organisation and other sources to track customer behaviours and preferences, which enhances the ability of the companies to offer a unique experience for all customers. The research gap emerging in this context occurs in the lack of adequate insights into how personalisation is considered an imperative across different cultures and how the AI assistants used in e-commerce are designed to foster it premised on each user's unique characteristics in a highly diverse customer base.

2.4.5 Attitude (AT)

The attitude individuals have towards a product or service has a substantial impact on their decision-making. Jain and Weiten (2020) describe attitude as a psychological construct that reflects individuals' feelings and beliefs when evaluating a particular service, product, event, phenomenon, or entity. Attitudes shape human behaviours and how individuals make decisions. Nevertheless, attitude is influenced by various factors such as the environment, social contexts, and access to information. Insights from Araujo et al. (2020) show that attitude can be positive or negative based on how an individual evaluates the subject. Positive attitudes are favourable toward the issue, while negative attitudes are unfavourable. Duffett (2020) attributes the varying attitudes that emerge among people to an individual's affective, cognitive, and behavioural aspects. Focusing on adopting and using new technologies, Xiao et al. (2019) determined that attitudes tend to be consistent among people with similar characteristics. However, some individuals within a group can change their attitude due to their experience or access to new information. Furthermore, Ajzen (2020) argues that in the context of the theory of planned behaviour, attitudes are subjective, which implies that the perceptions held by one person concerning a particular subject can differ significantly from those of another person. In the cultural context, Rawlings (2020) suggests that attitude can be deeply ingrained in one's beliefs that emerge from cultural influences. Such individuals are more likely to practice behaviours that align with their positive attitudes towards something while avoiding what contradicts their cultural beliefs. The gap in research emerging in this context is the lack of adequate insights that reflect how the Eastern and Western cultures and belief systems shape individuals' attitudes towards using AI assistance in e-commerce. Understating culture's influences on beliefs about AI assistance can influence positive attitudes and behaviours in how individuals utilise such services.

2.5 Chapter Summary

This chapter has reviewed previous research on adopting AI assistants and cross-cultural views. It began with a brief history of chatbots, presenting its main components and discussing how it has impacted various domains. This was followed by a discussion of empirical studies on general AI assistant adoption, particularly e-commerce. Furthermore, the cross-cultural perspectives on technology adoption were discussed in detail. The critical factors applied in the AI assistant adoption were described in detail: perceived usefulness, perceived ease of use, interactive communication, personalisation, and attitude.

An analysis of prior studies revealed a significant void in the literature, specifically, the dearth of research and conflicting evidence concerning the intention to use AI assistants. Furthermore, empirical research on this topic from the viewpoints of both users and non-users in the e-commerce domain is notably scarce. There is also a limited body of research that compares the attitudes and intentions of Western and Eastern consumers regarding the use of AI assistants. Therefore, the anticipated outcomes of the current study aim to address and bridge this gap by offering original and comprehensive data on the intentions of users and non-users to utilise AI assistants among global e-commerce consumers.

Chapter 3. Theoretical Background and Research Model

The following section explores the theoretical foundations relevant to the adoption of technology and the acceptance of AI assistants. Special attention is given to elucidating the foundational aspects of the Technology Acceptance Model (TAM), which serves as the fundamental framework for the investigative paradigm in this scholarly inquiry. Moreover, this chapter introduces the research model employed in the current study to address the gaps identified in the literature in Chapter 2. Additionally, hypotheses derived from the research model are articulated in this chapter, accompanied by a presentation of the pertinent literature for each. This chapter theoretically develops the research hypotheses through theoretical linkages in the hypothesis development section. The research model of this study is presented in Section 3.2. The summary of the research hypotheses is presented in Section 3.4. Finally, Section 3.5 concludes this chapter with a summary.

3.1 Theoretical Background

Businesses increasingly apply emerging technologies to meet their customers' needs. Therefore, its successful development is based on customers' attitudes towards using them (Guo & Luo, 2023; Foroudi et al., 2018). AI assistants remain in their nascent stage, characterized by limited scope and capabilities. Consequently, the exploration of AI assistants and their utilisation has emerged as a compelling subject within scientific research, particularly over the past decade. However, existing studies are constrained, omitting entire regions and yielding contradictory results on certain factors (Balakrishnan & Dwivedi, 2024; Collins et al., 2021). Some critical theoretical backgrounds that can help explain customers' attitudes and behavioural intentions in this context are; the TAM, a widely used model in technology adoption that explains users' acceptance of new technologies (Singh et al., 2024; Li, 2023; Wang et al., 2023a). The TAM model is proposed and derived from the theory of reasoned action (TRA) (Fishbein, 1979). The TRA theory proved that pre-existing consumer attitudes successfully predict and explain behavioural intentions that lead to a specific behaviour (Davis, 1989). Figure 3.1 presents the original factors of the TRA model: attitude toward behaviour, subjective norms, and behavioural intention.

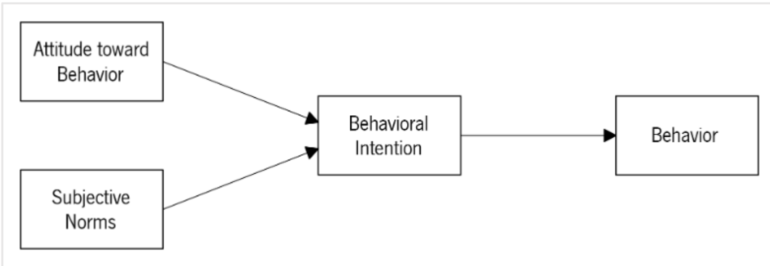

Figure 3.1. The TRA Model

Source: Ajzen & Fishbein, 1980

The primary purpose of the TAM model is to explain how internal factors, such as individuals' attitudes and intentions, are affected by external factors. The factors of the TAM can be observed in Figure 3.2. It suggests that users' attitudes and intentions to use technology are determined by two primary factors: perceived usefulness and ease of use. However, Davis (1989) has not measured a critical example of external factors and mentioned that users' general characteristics could be an affected external factor. Although different researchers have developed several new models for technology acceptance, the importance of the TAM model is still recognised by both academic and industrial researchers, especially in the AI assistant use field (Xiong et al., 2024; Wang et al., 2023a; Sciarelli et al., 2022; Chi, 2018; Zarouali et al., 2018).

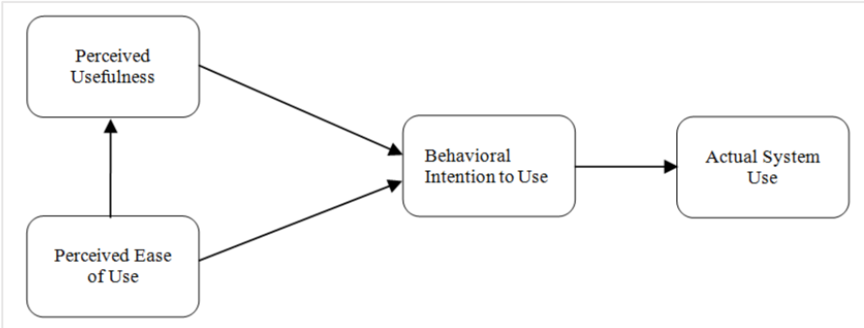

Figure 3.2. The TAM Model

Source: Naeini, 2012, p. 5288

Consequently, this section comprehensively synthesises pertinent scholarly works concerning utilising the TAM model in the context of novel technology assimilation and using AI assistants. This evaluative examination is the foundation for formulating a suitable conceptual framework for the current research. Moreover, it aids in the judicious selection of factors delineated within the literature as the most auspicious in elucidating the underlying determinants of intent to employ AI assistants, specifically from the vantage point of online shoppers. The ensuing enumeration expounds upon the principal rationales driving the integration of the TAM model in this study.

1. The TAM model is specifically formulated to assess the propensity of individual users to embrace a particular technology, in contrast to the Unified Theory of Acceptance and Use of Technology (UTAUT), as shown in Figure 3.3, which operates at the organisational level (Wang et al., 2023a; Ammenwerth, 2019; Lai, 2017). Hence, the present study is grounded in examining individual customers' perceptions, elucidating the rationale behind the preferential suitability of the TAM model for adoption.

2. The TAM model is recommended to be used where the acceptance of novel technology innovations is nascent (Acikgoz & Vega, 2022). This proposition is particularly pertinent within emerging technological advancements, such as AI assistants in the e-commerce domain, which are progressively gaining prominence for augmenting customer service and online shopping

experiences. The intricate dimensions of AI assistants' functionalities elucidate consumers' adoption behaviours concerning their utilisation in the e-commerce sector, which remains multifaceted (Li & Wang, 2023; Adam et al., 2021). Notably, the study encompasses a cohort of e-commerce consumers who have yet to engage with this technological paradigm, positioning them as nonusers. Because of these circumstances, the employment of the TAM model is advocated as an appropriate analytical framework.

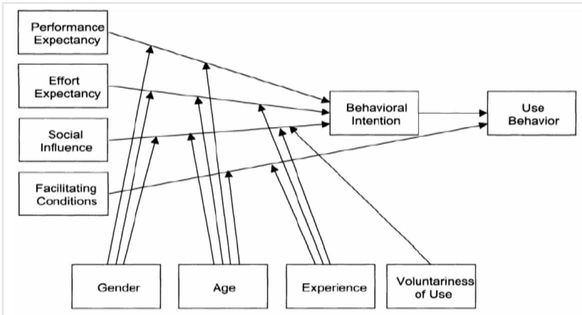

Figure 3.3. The UTAUT Model

Source: Venkatesh et al., 2003

Meanwhile, understanding users' attitudes and acceptance of technology is crucial for ensuring its successful adoption and implementation. It posits that two primary factors influence user acceptance: Usefulness and Ease of use. These factors are crucial in shaping consumers' attitudes about technology, ultimately influencing their opinions and behaviours regarding technology adoption (Kelly & Palaniappan, 2023). Usefulness refers to the degree to which consumers believe new technology will enhance their experience and provide tangible benefits (Eleonora & Loredana, 2012). In the context of shopping assistants, customers are likely to form positive beliefs if they perceive that AI technology can offer personalised product recommendations, streamline the shopping process, and save time and effort (Jan et al., 2023; Ameen et al., 2021). This perceived usefulness is influenced by various factors, such as the assistant's ability to understand customer preferences, its accuracy in suggesting relevant products, and its capacity to adapt to individual shopping behaviours over time (Ho & Chow, 2023). Similarly, perceived ease of use is another critical factor in shaping consumers' beliefs about an emerging technology (Huda, 2023). It relates to how users perceive that interacting with the technology is effortless and intuitive (Malodia et al., 2021). Perceived ease of use is vital. Customers are more likely to have positive opinions if they find the technology easy to navigate, understand, and incorporate into their routines (Jo, 2022) and shopping activities using AI assistants (Kautish et al., 2023). Moreover, it influences users' perceptions of the technology's usefulness, as the more manageable the system, the greater its utility can be (Mikalef & Gupta, 2021). Factors contributing to this perception include the assistant's interface design, conversational capabilities, and the absence of complex or confusing processes. These factors are selected based on the understanding that users' beliefs and attitudes significantly influence their intentions to adopt and continue using technology, such as mobile applications (Galetsi et al., 2023), social media (Wang et al., 2023b), virtual reality (Lv et al., 2022), and AI shopping assistants (Klaus & Zaichkowsky, 2022).

According to TAM, positive beliefs in both usefulness and ease of use lead to a positive attitude toward the technology, which, in turn, drives the intention to use the technology (Teo et al., 2009). Thus, by examining and understanding customers' attitudes to perceived usefulness and ease of use, businesses can identify the determinants of their opinions and adjust their AI shopping assistants to effectively meet customer needs and expectations. Moreover, other theoretical perspectives complement TAM in understanding the significance of perceived usefulness and ease of use in shaping customers' opinions toward AI shopping assistants. The customer experience concept emphasises that a positive experience is fundamental to influencing customer opinions and building loyalty (Srivastava & Kaul, 2016). A user-friendly and useful AI shopping assistant can enhance the customer experience, leading to more favourable opinions and increased usage (Ruan & Mezei, 2022; Zimmermann et al., 2023).

Furthermore, the Social Exchange Theory (SET) highlights the impact of social interactions with AI shopping assistants, affecting customers' satisfaction (Jiang et al., 2022). Additionally, the Theory of Reasoned Action emphasises subjective norms and the influence of the social environment on customers' attitudes (Roh et al., 2023). Meanwhile, trust shapes customers' opinions toward AI shopping assistants. Customers' attitudes are influenced by their confidence level in the AI assistant's reliability, security, and competence. Trust is built over time through positive experiences and consistent performance of the AI shopping assistant in meeting customers' needs and preferences (Pitardi & Marriott, 2021). Moreover, users' technology skills and ethical concerns factors also shape customers' opinions toward AI shopping assistants (Mantelero, 2022). Customers with different technological skills may have varying attitudes toward AI and personalised shopping experiences (Pillai et al., 2020). Ethical concerns, such as data privacy and transparency in AI decision-making processes, can influence customers' opinions positively or negatively, depending on how well companies address these issues (Aldboush & Ferdous, 2023).

Similarly, interactive communication and personalisation also affect customer attitudes and lead to the establishment of good behavioural intentions (Kim & Gambino, 2016). The theoretical background for interactive communication and personalisation is crucial in shaping customer attitudes and fostering positive behavioural intentions toward a technology (Chandra et al., 2022; Mariani et al., 2023). In the context of AI assistants, through interactive communication, AI assistants engage in dynamic and responsive interactions with users as two-way communication (Guzman & Lewis, 2020), fostering a sense of connection and perceived social presence, leading to heightened trust and likability (Tsai et al., 2021). In contrast, as contradictory results, Chung et al. 2020 have found that communication competence does not affect customer satisfaction. Personalisation of service reflects an individual's interests and preferences so that with a greater depth of personalisation, the content will be more relevant and useful (Serrano-Malebran & Arenas-Gaitan, 2021). Despite users' concerns over personal information leakage in the technology environment, individuals' needs for personalised services are increasing, creating a conflicting phenomenon (Lee, 2019). Drawing from theories like the TAM, SET, and personalisation, the positive user experiences facilitated by interactive communication (two-way communication) and personalisation lead to increased perceptions of AI assistants as valuable and reliable tools, resulting in the establishment of favourable behavioural intentions, such as continued usage and word-of-mouth recommendations, which ultimately contribute to the successful integration of AI assistants into users' lives (Gao & Huang, 2019; Khalid & Ali, 2017).

The factors underlying the selection of behavioural intentions concerning the adoption of AI within the context of e-commerce are grounded in pertinent theoretical constructs. The rationale for including these factors in the study is substantiated by their alignment with established theoretical frameworks and empirical evidence from existing literature. Drawing from the TAM, the chosen factors encapsulate critical determinants influencing users' inclinations to engage with AI assistants in e-commerce settings. These factors encompass perceived usefulness, perceived ease of use, social influence, and facilitating conditions. These dimensions have been widely acknowledged and explored in prior research as influential predictors of users' intentions to adopt and use technological innovations.

The decision to incorporate these factors stems from their comprehensive coverage of the cognitive, social, and contextual aspects that underpin users' decision-making processes. Empirical support from seminal studies further reinforces their significance in elucidating the complexities of technology adoption, including AI assistants, in e-commerce. Through a synthesis of scholarly references and theoretical underpinnings, this study substantiates the rationale behind selecting these factors by elucidating the theoretical basis and explaining the linkage between the chosen factors and the phenomenon under investigation. However, understanding these theoretical elements is critical for organisations and developers seeking to increase customer adoption and usage of AI shopping assistants, which can enhance the overall e-commerce experience. Additionally, it is important to note that customers' opinions are diverse and multifaceted, so combining these theories with personalisation is necessary for a comprehensive analysis. Social, consumer, and contextual factors will also significantly shape customers' attitudes toward AI shopping assistants.

3.2 Research Model

Figure 3.4 shows the research model designed for this study. The proposed model examines consumers' attitudes and intentions towards using Artificial Intelligence (AI) service shopping assistants in e-commerce as the primary dependent variables. This study validates the relationship between attitude and usage intention in commerce AI assistants. Further, this study has explored and added additional constructs, which are perceived usefulness, perceived ease of use, and AI shopping assistant capabilities (interactive communication and personalisation), to make the research model more meaningful in understanding consumers' acceptance and usage of AI assistants in e-commerce. Table 3.1 summarises the definitions of the critical factors used in the research model.

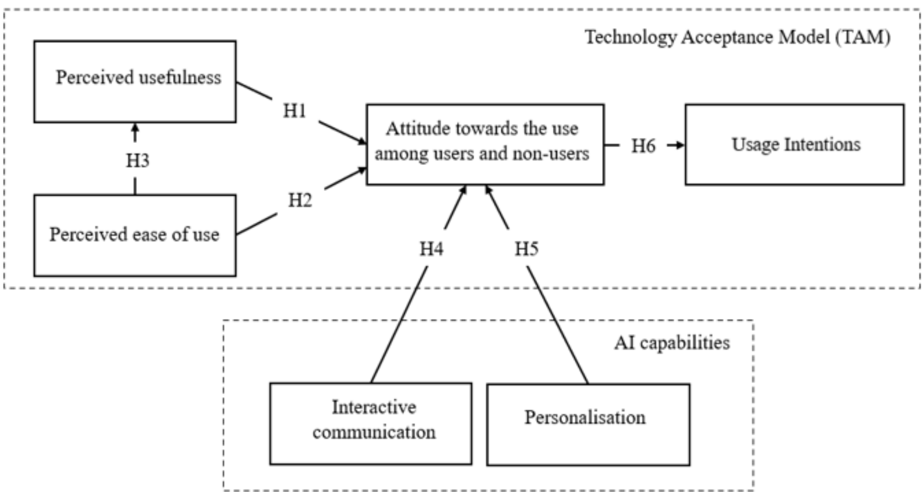

Figure 3.4. Research Model

The model was based on the hypothesis that consumers' attitudes towards AI assistants are the fundamental determinant driving their decision to adopt these technologies, consequently impacting their tangible utilisation of the AI assistant. The perceived usefulness and ease of use encapsulate an individual’s belief in the potential of AI assistants to augment task performance or productivity/efficiency, accompanied by the notion that interaction with AI assistants will be devoid of undue complications. Moreover, within this theoretical framework, the attitude held by an individual towards the utilisation of AI assistants encapsulates their favourable or emotional disposition. Concurrently, behavioural intention pertains to an individual's ultimate decision to adopt AI assistants, contingent upon their orientation. Prior research has found that belief, attitude, and purpose are strongly related and have significant relationships (Foroughi et al., 2019). However, previous studies have argued that perceived ease of use and perceived usefulness may only partially reflect consumers' attitudes, necessitating an investigation of additional predicting factors (Ladkoom & Thanasopon, 2020). Therefore, this research tested a model that assesses other elements from the literature, such as AI shopping assistant capabilities, which could influence consumers' attitudes toward AI shopping assistants.

The research model included seven hypotheses concerning the relationships among the model’s distinct components. The initial hypothesis posited a favourable association between usefulness and attitudes toward adopting AI assistants among users and non-users. The second hypothesis postulated a positive relationship between the attributes of AI assistants and the corresponding attitudes towards their ease of use among users and non-users. The third hypothesis inferred that perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants. The fourth hypothesis perceives interactive communication positively influences the attitudes of users and non-users towards the use of AI assistants. The fifth hypothesis conjectured that personalisation positively influences the attitudes of users and non-users in utilising AI assistants in e-commerce. The sixth hypothesis inferred that attitude positively impacts behavioural intention to use AI assistants among users and non-users. The seventh hypothesis postulated that the relationships among the primary factors influencing the intention to use AI assistants in e-commerce differ between Western and Eastern cultures. The research model in this study is used to explain the adoption of using AI assistants. Therefore, the research model is significant and distinguished compared to previous studies for several reasons:

1. Focus on Consumer Perceptions: The research model focuses on consumer perception and usage intentions. This focus is essential because it acknowledges that accepting AI platforms and their success depends on consumers' attitudes toward their adoption.

2. Simplicity: The research model is simple and easy to understand. It consists of only four key constructs: perceived usefulness, perceived ease of use, and AI capabilities (interactive communication and personalisation). This simplicity makes the research model accessible to researchers and practitioners.

3. AI applications: The research model specifically addresses the trended AI assistant technologies across global consumers, including users and non-users of AI assistants. This trended AI technology has helped establish the research model as an essential framework for understanding AI assistant adoption. Indeed, previous studies have investigated the effectiveness of chatbots among Facebook users (Zarouali *et al*., 2018). Still, they have not included AI capabilities, a critical factor before consumers' attitudes.

4. User Differences: The research model considers the consumers' differences toward using AI assistants in e-commerce from multiple perspectives, unlike recent studies focusing on just users and a specific cultural context (Lee & Lin, 2023; Shin, 2010).

Table 3.1. Definition of Factors Included in the Research Model

Constructs	Definition	Sources
Perceived usefulness and ease of use	*Perceived usefulness and ease of using AI shopping assistants are practical and effortless and will enhance consumers' productivity or task performance.*	Zarouali *et al.*, 2018
AI capabilities: Interactive communication and personalisation	*The extent to which AI shopping assistants facilitate two-way communication between consumers to provide personalised assistance and support tailored to their specific needs and preferences.*	Chung *et al.* 2020, Srinivasan *et al*. 2002
Attitude towards using	*Refer to the feeling or opinion towards using AI shopping assistants.*	Moon and Kim, 2001
Usage Intentions	*Refer to the willingness to use and continue using AI shopping assistants in the future and recommend them to others.*	Zarouali *et al.*, 2018

One major theoretical factor that drives customers' adoption and use of AI shopping assistants is their sense of usefulness and usability (Ajisoko, 2020; Maryanto & Kaihatu, 2021). Consumer utility beliefs are their assessment of how valuable and beneficial AI shopping assistants are in terms of increasing productivity and task performance. This opinion is based on the idea that AI assistants can provide helpful features such as tailored suggestions, efficient search functionality, and overall shopping ease (Ajisoko, 2020). Consumers are more likely to accept and use AI shopping assistants in their e-commerce activities if they are helpful. Similarly, ease-of-use perception heavily influences consumer adoption and use of AI shopping assistants. Ease of use refers to users' perceptions of how simple it is to interact with AI helpers and traverse their interfaces. Perceived ease of use impression is heavily influenced by intuitive design, clear information display, and simplicity of communication (Sudaryanto et al., 2023). Customers who view AI shopping assistants as user-friendly are more likely to have good attitudes regarding utilising them and are more likely to incorporate them into their shopping habits.

Another key theoretical issue is how AI shopping assistants promote two-way dialogue and customised consumer guidance (Huang & Rust, 2021). Interactive communication is the ability of AI assistants to participate in dynamic and responsive interactions with customers (Adam et al., 2021). This includes answering inquiries, clearing uncertainties, and offering real-time assistance. Interactive communication increases consumer happiness and perceptions of the AI assistant's effectiveness by fostering a sense of involvement and trust. Personalisation is another essential feature of AI shopping assistants. Personalised help means adapting advice, ideas, and product offers to meet consumers' requirements, preferences, and interactions (Suresh et al., 2023). AI shopping assistants increase consumer happiness and establish relevance by offering individualised experiences, which can favourably affect attitudes and intentions toward adopting the technology (Zimmermann et al., 2023). These factors are essential in shaping users' emotional connection and perceived social presence with the AI assistant (Zhang et al., 2021). By examining how interactive communication fosters dynamic and engaging interactions while personalisation tailors the experience to individual preferences, the researcher could explore how these aspects influence users' attitudes and subsequent behavioural intentions. Moreover, AI shopping assistants can be programmed to interact with consumers conversationally, using natural language processing to understand and respond to consumers' requests (Bahja, 2020). Personalised communication can enhance the consumer experience of using AI assistant platforms. Attitude towards using refers to consumers' overall perspective about using the AI shopping assistant. Understanding the predisposition and emotions users associate with AI assistants is pivotal in comprehending how receptive they are to integrating these tools into their daily lives.

Attitude is an individual's general feeling or opinion about using AI shopping assistants. It includes customers' evaluative judgments, emotional reactions, and attitudes about the worth and use of AI assistants (Pillai et al., 2020). Positive sentiments regarding AI shopping assistants are expected to be influenced by perceptions of usefulness, usability, interactive communication, and personalisation (Yin & Qiu, 2021). Attitudes affect consumers' readiness to accept and employ AI shopping assistants in e-commerce, impacting their intent to use them. Positive attitudes often lead to greater acceptance and willingness to continue using AI assistants, while negative attitudes may hinder adoption and create barriers (Acikgoz et al., 2023). Finally, the factor of behavioural intention reflects users' inclination to use AI assistants in the long run. Behavioural intention is the likelihood that consumers will use AI shopping assistants in the future and recommend them to others. It denotes expected conduct based on people's views, perceived usefulness, and subjective standards. Consumers with favourable beliefs and stronger perceptions of service, usability, interactive communication, and personalisation are more likely to acquire strong intentions to continue using AI shopping assistants and to urge others to do the same.

Analysing the attitudes of users and non-users towards AI, as well as comparing these perspectives between Western and Eastern consumers, provides valuable insights into the cultural and experiential factors that shape individual perceptions of technology. Users often exhibit a higher level of comfort and familiarity with AI due to direct interactions, which can result in a more nuanced understanding of its benefits and limitations (Jiang et al., 2022). Conversely, non-users may hold reservations rooted in uncertainty or misinformation (Kreutzer & Sirrenberg, 2020). When considering Western and Eastern consumers, different societies, such as the West and East, often contrast their attitudes toward Technology and AI (Jecker & Nakazawa, 2022; Lim et al., 2021). Western societies, typically characterised by fast-paced technological adoption, may showcase a more diverse range of attitudes due to varying levels of innovation and education. Meanwhile, Eastern cultures might have unique societal expectations that could demonstrate attitudes influenced by communal values or past technological experiences (Frank et al., 2021). Therefore, this mode tested a difference between

Western and Eastern consumers regarding their attitudes and intentions to use this service for e-commerce.

Incorporating these factors into this study offered a holistic and robust analysis of the complex dynamics between users and AI assistants. Examining how usefulness, ease of use, AI assistant capabilities, and attitudes collectively influence behavioural intentions leads to identifying key drivers and barriers to successful AI assistant adoption. It offered valuable insights into the mechanisms that lead to positive outcomes, such as increased satisfaction, trust, and continued usage, which are vital for successfully establishing and integrating AI assistants in e-commerce. Through systematically exploring hypotheses, investigators can gain enhanced insights into the pivotal determinants that influence the adoption of AI assistants. This process subsequently empowers the formulation of strategies to enhance the embracement and integration of sophisticated AI assistants within online retailers and e-commerce enterprises. In light of these findings, marketing practitioners are impelled to cultivate and refine their customer service stratagems, as these measures effectively facilitate consumers' interactions with e-service platforms, consequently mitigating the temporal extent devoted to online product exploration and shopping undertakings.

3.3 Hypotheses

The adaptable nature of IS adoption research models facilitates their application across various technological domains, allowing for the incorporation of context-specific determinants. As a result, examining the adoption of AI assistants in e-commerce involves considering several factors that have proven to be impacted from e-commerce consumers' perspectives, affecting both users' and non-users' attitudes. These key factors were discussed in Chapter 2, and their hypotheses were elaborated on in the following sections.

3.3.1 Perceived Usefulness and Attitude

The concept of perceived usefulness in the context of AI deployment within e-commerce holds significant implications for individuals' attitudes toward its utilisation. The perceived usefulness of AI technologies, encompassing their potential to enhance decision-making, optimise shopping experiences, and provide personalised recommendations, fundamentally shapes consumers' attitudes and receptiveness towards incorporating such technologies into their online shopping practices. A positive perception of AI's usefulness can foster a favourable attitude, engendering a willingness to embrace and engage with AI-driven features in e-commerce platforms and reinforcing the symbiotic relationship between perceived usefulness and user attitudes in this dynamic digital landscape.

In addition, recent studies have shown that perceived usefulness positively influences technology adoption and acceptance (Ohk *et al*., 2015). Additionally, past empirical evidence has demonstrated that usefulness perception can influence consumer attitudes, such as attitudes toward social media adoption (Alduaij, 2019). Moreover, the study's findings demonstrate that each proposed hypothesis has yielded favourable and statistically significant outcomes. In contrast, the variable perceived usefulness emerged as the most robust predictor influencing the individual's overall experiential outcome for using chatbots (Lubbe & Ngoma, 2021). In addition, another study's results also reveal that factors such as the perceived usefulness of the mobile app have noteworthy effects on the user's intentions to employ the mobile application and their overall attitude towards it (Hasan, 2022). Nevertheless, trust, personal innovativeness, and attitude solely impacted the inclination toward usefulness.

Meanwhile, including "usefulness" in studies about using AI in e-commerce is motivated by its significance in shaping individual attitudes. This factor is recognised as pivotal due to its potential to influence how individuals perceive the applicability and advantages of AI within the e-commerce context. Investigating the relationship between usefulness and attitude among users and non-users helps understand how the perceived usefulness of AI technologies may contribute to shaping overall positive or negative attitudes toward their adoption and integration in e-commerce settings (Teodorescu et al., 2023). This relationship is expected to provide valuable insights into the underlying mechanisms that drive individuals' behavioural intentions and decision-making processes in AI use in e-commerce (Rodgers et al., 2023). In summary, perceived usefulness has been approved as a strong predictor of how people feel about adopting AI assistants for various tasks, including online shopping. Nevertheless, there remains a lack of evidence regarding its impact on the intention to use AI assistants among both non-users and users. To test this, the following hypotheses were developed:

H1. Perceived usefulness positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

3.3.2. Perceived Ease of Use and Attitude

The perception of the ease with which AI technologies can be employed within the context of e-commerce significantly shapes individuals' attitudes toward their utilisation. This cognitive assessment of the convenience and ease of use of AI-driven tools and systems, ranging from personalised product recommendations to virtual shopping assistants, profoundly influences stakeholders' inclinations to embrace and engage with such technological solutions (Ho, 2021). Consequently, enhanced perceived ease of use tends to foster a more positive attitude among consumers and potential users, fostering an environment conducive to the widespread acceptance and integration of AI advancements in e-commerce (Kumar et al., 2019). Furthermore, the perceived ease of use directly impacts the intention of customers to make a purchase (Nofirda & Ikram, 2023). Additionally, trust positively impacts perceived ease of use, correlating with perceived usefulness and user attitudes towards AI (Wang et al., 2023a). In contrast, the empirical evidence suggests that perceived ease of use does not correlate statistically with the dependent variable (Tan & Lim, 2023).

The significance of the "ease of use" factor in utilising AI stems from its pivotal role in determining the successful adoption and integration of AI technologies by individuals and organisations. This factor directly influences the accessibility, comprehensibility, and user-friendliness of AI systems, affecting users' willingness and efficiency to engage with and harness AI capabilities. A high degree of ease of use in AI systems is instrumental in mitigating potential barriers that impede the acceptance and effective utilisation of these advanced technologies. Complex and unintuitive AI interfaces or applications can lead to user frustration, resistance, and decreased adoption rates. On the contrary, when AI solutions are designed with a focus on ease of use, they empower a more comprehensive range of users, including those with limited technical expertise, to seamlessly interact with AI-driven functionalities. Moreover, the ease-of-use factor enhances productivity and task performance. Intuitive AI interfaces enable users to quickly grasp the functionalities and features of AI systems, thereby expediting the learning curve and facilitating proficient utilisation. This, in turn, bolsters users' confidence and motivation to leverage AI tools to their full potential, leading to improved decision-making processes and outcomes.

From an organisational standpoint, the ease of use of AI technologies can drive higher levels of adoption across various departments and personnel, fostering a culture of innovation and efficiency. This can result in quicker integration of AI-driven insights into business strategies and operations, ultimately yielding competitive advantages and improved operational outcomes. To succinctly encapsulate, perceived ease of use emerges as a robust precursor that delineates the disposition towards embracing AI assistants across multiple domains, including online shopping and its associated technologies. Nevertheless, a discernible dearth of substantiated indications pertains to its sway upon the proclivity of both non-users and users to engage with AI assistants. Accordingly, the following hypothesis was tested:

H2: Perceived ease of use positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

3.3.3. Perceived Ease of Use and Perceived Usefulness

The assessment of AI assistants' efficiency in e-commerce is intrinsically tied to two pivotal dimensions: perceived ease of use and usefulness (Wang et al., 2023a). The perceived ease of use encapsulates users' perceptions of the intuitive nature and simplicity of interacting with AI-driven systems, shaping their attitudes and predisposition towards employing such technology. Simultaneously, perceived usefulness encompasses how AI assistants are perceived as capable tools that enhance efficiency, convenience, and effectiveness within e-commerce contexts. These dimensions collectively shape individuals' inclinations and behaviours regarding adopting and accepting AI assistants in e-commerce settings. Meanwhile, Jannach et al. (2021) found that trust in AI is materially shaped by variables encompassing transparency, acquaintance with diverse AI applications, and the perceived usefulness and ease of use of AI recommendation systems. In order to foster extensive approval and integration among users, e-commerce enterprises must accord paramount importance to cultivating trust in these emergent technological paradigms (Teodorescu et al., 2023). Moreover, Noreen et al. (2023) demonstrated a noteworthy and affirmative correlation between the intention to embrace AI and critical factors encompassing perceived usefulness and ease of use of AI technology.

The intricate interplay between the perception of ease of use and perceived usefulness in employing AI within e-commerce warrants an examination of its mechanisms and underlying rationales. How perceived ease of use influences perceived usefulness in using AI in e-commerce can be elucidated through cognitive and psychological processes and has a favourable impact on the perception of usefulness (Mollick et al., 2023). When users perceive an AI-driven system or platform as easy to navigate and interact with, they are more likely to develop a positive cognitive disposition towards the technology. This positive cognitive stance can enhance their perception of the system's usefulness. Simplified and intuitive interactions engender a sense of proficiency and mastery, subsequently fostering a perception that AI technology is efficacious in achieving the intended goals within the e-commerce domain. Furthermore, a perceived easy-to-use diminishes cognitive load and reduces the mental effort required for engagement. Reducing cognitive burden liberates cognitive resources, enabling users to process information and evaluate the system's utility more effectively (Koć-Januchta et al., 2022). Consequently, perceived ease of use enhances the cognitive efficiency of users, resulting in an amplified perception of the AI's overall usefulness.

The rationale for this influence can be attributed to the principle of cognitive alignment, where congruence between the cognitive demands posed by the technology and the cognitive capability of the user fosters a harmonious interaction. The lessened cognitive friction arising from a user's perception of ease aligns with the cognitive processes required for appraising usefulness. Users tend to evaluate the utility of AI within e-commerce based on their cognitive investment, wherein reduced cognitive load stemming from the ease of use aligns with the positive valuation of the technology's usefulness. In summation, the constructs of perceived usefulness and ease of use have demonstrated robust predictive capabilities concerning the disposition towards adopting AI assistants across diverse domains, including pertinent technologies within online commerce. Nevertheless, an empirical void remains concerning their potential impact on the inclination to utilise AI assistants, both for individuals unacquainted with their usage and those already versed in their application. In order to probe into this phenomenon, the subsequent set of hypotheses has been formulated:

H3: Perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants.

3.3.4. Interactive Communication and Attitude

Research has shown that AI assistant characteristics and interaction styles are crucial in human–chatbot communication (Wilkinson et al., 2021; Roy & Naidoo, 2021; Liew et al., 2021). For example, the social characteristics of AI assistants can meet users' expectations, which can help to avoid frustration and dissatisfaction (Chaves & Gerosa, 2021). Li and Wang (2023) found that informal language styles of AI assistants can help create a more natural and interpersonal communication experience with consumers, ultimately leading to positive service outcomes. While some studies on digital service assistants have found that the complete communication skills of these tools do not impact customer satisfaction (Chung et al., 2020), the literature has consistently indicated that AI assistants should be designed with expertise capabilities in mind for e-commerce (Petersson et al., 2023; Liew et al., 2021). Therefore, interactive communication is adopted from the marketing and communication literature to demonstrate the expert level of AI assistants in e-commerce. Previous empirical studies have found that interactive communication predicts attitudes toward online communicators (Lee et al., 2015). Meanwhile, Interactive communication notably influences attitudes towards AI utilisation in e-commerce due to its capacity to personalise interactions, enhance transparency and understanding, empower users, and foster social presence. Understanding these dynamics is essential for e-commerce platforms seeking to optimise user experiences and adopt AI-driven features (Haleem et al., 2022; Nicolescu & Tudorache, 2022). Therefore, the limited number of studies on the use of AI assistants and related fields, along with their varied outcomes, raises an open question regarding the impact of the communication skills of AI assistants on the attitudes and usage intentions of both users and non-users in e-commerce. Accordingly, the following hypotheses were tested:

H4: Interactive communication positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

3.3.5. Personalisation and Attitude

Personalisation in e-commerce applications gives the power to modify the service's characteristics to suit their needs or preferences (Srinivasan *et al.*, 2002). Meanwhile, AI facilitates personalisation in various facets, including personalised profiling, navigation, nudges, and retention strategies, which are discernible across the customer journey's sequential phases. These personalised AI-driven interventions come to the fore in reaction to the challenges encountered throughout this journey (Gao & Liu, 2022). The application of personalisation exerts a favourable impact on consumer attitudes and their intentions to share personal information with a digital assistant (Kronemann et al., 2023). Meanwhile, personalisation significantly impacts shaping individuals' attitudes towards AI deployment in the e-commerce landscape. This influence is underpinned by relevance, efficiency, and psychological perceptions of companionship. Understanding these mechanisms provides valuable insights for e-commerce businesses aiming to enhance user acceptance and engagement with AI-driven systems.

Current e-commerce AI platform developments are focused on offering customisation options to meet individual preferences (Wu *et al*., 2020). For example, Gucci uses a chatbot to send personalised advertisements to target customers interested in customised products (Chung *et al*., 2020). Much consumer research has found that customisation positively impacts consumers' attitudes toward marketing communication and mobile advertising (Jeong *et al*., 2020). Furthermore, recent findings showed that customisation could significantly impact attitudes toward using mobile commerce applications (Marinkovic & Kalinic, 2017). Moreover, the empirical investigation centred on a cohort of female fashion retail consumers in the United Kingdom subjected to such promotional propositions. The findings from this case study delineate that these consumers exhibit a proclivity for seeking price reductions on items of interest, alongside an aspiration for enhancing their in-store experiences. However, they exhibit aversion towards disruptions and generic promotional overtures. Additionally, a conspicuous inclination towards self-governance becomes apparent, coupled with endeavours to exert control over private information's divulgence and ameliorate the quality of recommendations received. Importantly, our analysis brings inherent incongruities within customers' anticipations about personalised interactions, necessitating the tracking of geographic coordinates (Canhoto et al., 2023). Moreover, investigations indicate that consumers swiftly adopt AI for their daily activities because it can afford individuals prompt and valuable information access. Furthermore, AI technologies have demonstrated their capability to cater to customers' personalisation by providing contextually pertinent and meticulously tailored content, all while being disseminated instantaneously (Brill et al., 2022).

A limited body of research about the utilisation of AI assistants and its associated domains, coupled with inconclusive findings, has given rise to an unresolved inquiry concerning the impact of personalised interactions demonstrated by AI assistants on the attitudes and intention to use, both among users and non-users of AI assistants within the area of e-commerce. Consequently, the present study examined the following hypotheses:

H5: Personalisation positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

3.3.6 Attitude and Intention

Consumers' attitudinal experience using an AI shopping assistant positively relates to their behavioural intention, especially their usage intention. The relationship between attitude and use intention is well-documented in IS research (Harasis *et al*., 2018). More precisely, this study focuses on 'consumers' choice to use AI assistants to communicate with online retailers for e-commerce. Recent studies have found that attitude is a crucial factor influencing consumers' intention to use virtual AI as a shopping assistant (Kasilingam, 2020). The theory of reasoned action and technology acceptance model states that the user's behavioural intention to use an information system determines user acceptance and actual behaviour (Davis, 1989). Behaviour refers to a consumer's intention to take specific actions (Purwanto & Loisa, 2020). Therefore, the intention will determine use behaviour (Davis, 1989). Purwanto and Loisa (2020) found that mobile banking systems positively and significantly predicted the actual banking system use behaviour. Moreover, Tandi and Questier (2014) also found that the behavioural purpose of using communication systems predicted actual usage. Thus, this research hypothesis is that the attitudes will positively influence the usage intentions of users and non-users toward using AI assistants in e-commerce. (H6).

The discernible distinction in consumers' attitudes and behavioural intentions between Western and Eastern cultural contexts regarding adopting and utilising technologies can be attributed to cultural, societal, and psychological factors. Western cultures, characterised by individualism (Kim et al., 1994) and valuing autonomy, often foster an environment that encourages rapid technology adoption, as it aligns with notions of self-expression and personal efficiency (Leidner & Kayworth, 2006). In contrast, Eastern cultures, which frequently emphasise collectivism and social harmony (Triandis, 2015), tend to exhibit a more cautious approach towards technology integration, valuing stability and tradition (Erez & Earley, 1993). Furthermore, cultural dimensions such as uncertainty avoidance and power distance influence the level of comfort individuals feel when engaging with novel technologies. Psychological theories, including the TAM, suggest that cultural norms and values shape cognitive and affective responses to technology (Lai et al., 2016; Srite & Karahanna, 2006). Additionally, variations in language, communication styles, and aesthetics shape perceptions of technology. These multifaceted factors collectively contribute to the distinct patterns of consumers' attitudes and intentions in Western and Eastern cultural contexts when adopting and utilising technologies. Accordingly, the model was tested between Western and Eastern groups to explore the differences in the relationship between all antecedents and intention towards the use of AI assistants. Therefore, this research hypothesises that the relationships among the primary factors influencing the intention to use AI assistants in e-commerce differ significantly between Western and Eastern cultures (H7). Table 3.2 outlines the hypotheses.

Table 3.2. Summary of Hypotheses

Main Question	Sub-questions 1.1 – 1.7	Hypotheses
What factors influence individuals' intention to use AI assistants in e-commerce among users and non-users, and are there significant differences in these factors' impact when comparing Western and Eastern cultures?	How does perceived usefulness affect the attitudes of users and non-users towards using AI assistants in e-commerce?	**H1.** Perceived usefulness positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.
	How does perceived ease of use affect the attitudes of users and non-users towards using AI assistants in e-commerce?	**H2.** Perceived ease of use positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.
	How does perceived ease of use affect the perceived usefulness of users and non-users of AI assistants in e-commerce?	**H3.** Perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants.
	How does interactive communication affect the attitudes of users and non-users towards using AI assistants in e-commerce?	**H4**. Interactive communication positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.
	How does personalisation affect the attitudes of users and non-users towards using AI assistants in e-commerce?	**H5.** Personalisation positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.
	How does attitude affect the intentions of users and non-users towards using AI assistants in e-commerce?	**H6**. The attitudes will positively influence the usage intentions of users and non-users toward using AI assistants in e-commerce.
	Do significant differences exist in the relations among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultures?	**H7.** The relationships among the primary factors influencing the intention to use AI assistants in e-commerce differ significantly between Western and Eastern cultures.

3.4 Chapter Summary

This chapter has described the theoretical models pertinent to technology adoption and the acceptance of AI assistants. It also described factors used in previous associated studies to establish the theoretical linkages of the research model. As mentioned above, the research model was based on the TAM Model, and the researcher intended to extend it by incorporating AI assistant capabilities while considering user and cultural differences that have been found to be impactful for AI assistant adoption in e-commerce. Furthermore, seven research hypotheses have been developed for empirical testing based on the theoretical arguments concerning the main research factors, such as usefulness, ease of use, interactive communication, personalisation, and usage intentions. The following chapter discusses the research methodology adopted for this study.

Chapter 4. Research Methodology

4.1 Research Paradigm

Years of scientific inquiries have led to the development of various considerations for researchers to account for in establishing how they should engage in a specific investigation. These approaches have been grouped into research paradigms that have emerged and developed across different disciplines. According to Mackenzie and Knipe (2006), the research paradigm alludes to the framework that integrates the theories and practices aligned with the researcher's discipline to develop an appropriate research plan. Antwi and Hamza (2015) suggest that the research paradigm alludes to the set of ideas, beliefs, or understanding that sets the basis on which theories and practices function in creating or improving knowledge. The research paradigm is premised on the aim of the study, research objectives, questions, instruments and measurements, and analysis methods. According to Mackenzie and Knipe (2006), adopting a research paradigm is critical for any study because it clarifies the investigation and improves the quality of the methods and analysis employed in developing knowledge.

Furthermore, Antwi and Hamza (2015) highlight that the research paradigms reflect the beliefs, assumptions, and biases that impact the research process, outcomes, and application of the findings. There are three key pillars of research paradigms. These are ontology, epistemology, and methodology. Ontology alludes to the nature of reality, which can be single or multiple realities. Epistemology focuses on the study of knowledge by highlighting how researchers can gain knowledge and how they can validate it. The methodology is how the research is conducted and validated to gain new knowledge. Therefore, the research paradigms offer insights into how ontology, epistemology, and methodology are integrated to develop a practical structure and process for conducting the investigation. According to Goduka (2012), the research paradigm establishes the philosophical basis that entails how data is collected and analysed to develop knowledge.

Although various research philosophies exist, the majority of the paradigms are premised on the positivism and interpretivism approaches. Alharahsheh and Pius (2020) note that positivism and interpretivism are key influences in developing other research paradigms due to their direct link to quantitative and qualitative research approaches. The variations between the two approaches highlight their unique strengths in addressing issues under investigation. According to Antwi and Hamza (2015), positivism and interpretivism present contrasting philosophies that guide social science investigations through different ontological and epistemological approaches. Positivism is described as a philosophical approach rooted in natural sciences that advocates for gathering and analysing empirical evidence using scientific methods. The underlying assumption in positivism is that investigating the social world should be accomplished by focusing on the regular patterns and laws in a phenomenon similar to what is experienced in the natural world using observations and measurements (Cecez-Kecmanovic, 2005). Positivism is objective, implying that researchers aim to eliminate bias and personal values in the research process. This is accomplished by applying quantitative methods to gather large volumes of data from large sample sizes to enhance the generalisation of the findings and conclusions. It also embraces deductive reasoning, which entails starting with a theory or hypothesis that can be tested using the data collected and analysed in the study (Casula et al., 2021). Interpretivism contrasts positivism as a philosophical approach that focuses on subjective meanings, assuming that reality is a social construct that can be understood from multiple perspectives. According to De Villiers (2005), interpretivism challenges the perceptions held by positivists by highlighting the importance of integrating the intricacies of human experiences and behaviours from the multiple layers emerging in the social context under investigation. Interpretivists demonstrate that researchers play a critical role in gathering and interpreting data from qualitative methods that foster a subjective approach for deeper exploration of meanings and contexts. Therefore, adopting interpretivism offers an opportunity to integrate human elements such as beliefs, actions, relationships, and interactions in developing new insights.

The current study seeks to demonstrate how AI assistants in e-commerce can be improved premised on the users' experiences with the technologies. Therefore, gathering quantitative and qualitative data is critical in addressing the research objectives. According to Kaushik and Walsh (2019), a pragmatic research paradigm is a philosophical approach that bridges the gap between positivism and interpretivism and offers an opportunity for researchers to integrate qualitative and quantitative research methods in the same study. Pragmatism is a problem-oriented approach that uses different research methods based on their appropriateness in addressing the research problem (Morgan, 2014). Although the pragmatic research philosophy could have been adopted in the current study, employing both positivist and interpretivist research philosophies offers a more strategic approach to addressing the research problem and influencing outcomes that substantially contribute to the wider social science field. In this context, addressing the research problem requires a sequential approach where quantitative data is employed in developing the basis for developing the qualitative investigation that, when the insights are integrated, can result in practical solutions for the research problem. The current study is pertinent for social sciences by demonstrating different research philosophies can be used in the same study. Moon and Blackman (2014) review that researchers in social sciences often focus on a single philosophical approach. This study challenges this by highlighting that a sequential approach can entail following different philosophical approaches to enhance the insights gained from each research methodology adopted.

Quantitative research refers to structured and systematic techniques used to gather and analyse numerical data that can be interpreted to explain a particular phenomenon. Quantitative studies entail measuring variables and establishing the relationships between them, leading to generalisations based on the statistical analysis conducted. Often, data collection entails administering surveys to large samples or conducting experiments that involve manipulating variables to gain insights into the cause-and-effect relationships. The statistical analysis includes descriptive statistics such as mean, median, and standard deviation and inferential statistics (Simpson, 2015). Qualitative research methods premised on interpretivism entail gathering non-numerical data that fosters an in-depth understanding of human experiences and social phenomena. Qualitative studies are effective in developing meanings and interpretations and in contextualising social experiences that are difficult to quantify. Qualitative data can be collected from secondary sources through literature review or document analysis and primary research involving interviews, focus groups, and observations in natural settings, among others (Kaplan & Maxwell, 2005). The quantitative and qualitative methods can be used in the same study through the mixed-method research methodology. This study adopts a mixed-method approach for its research methodology, integrating both quantitative and qualitative methods to encompass positivism and interpretivism perspectives in faithfully representing the phenomenon under investigation (Petter & Gallivan, 2004). Quantitative and qualitative methods can effectively complement each other within a mixed-method research design, a framework that aligns with critical realism. Critical realism emphasises understanding both observable regularities and the underlying causal mechanisms that shape phenomena (Mukumbang, 2023). This study adopts a mixed-method approach to explore the adoption of AI assistants in e-commerce, integrating quantitative surveys and qualitative interviews. The quantitative aspect follows a positivist approach, utilizing established theories to formulate hypotheses and employing surveys to quantify consumers' attitudes and intentions towards AI assistants. Concurrently, the qualitative component adopts an interpretivist stance, providing deeper insights into the survey results and exploring the contextual factors influencing adoption behaviours. This methodological pluralism not only enhances the breadth of understanding but also aligns with critical realism's goal of uncovering both the surface-level patterns and the deeper structures that influence technology adoption in real-world settings.

The primary emphasis is on a quantitative (positivist) approach, which involves studying well-established theories and pertinent literature to formulate hypotheses and a conceptual model. The conceptual model is subjected to quantitative analyses, utilising a survey method to gauge consumers' attitudes and intentions towards using AI assistants. Subsequently, a qualitative (interpretivist) approach is employed to provide supplementary insights that enhance the understanding of the quantitative results. Machine learning techniques were employed as a supplementary procedure for this type of analysis. Therefore, the research is accomplished through a sequential mixed methodology.

The mixed method research strategy using qualitative and quantitative techniques is widely used in information systems (IS) fields (Petter & Gallivan, 2004). According to Ivankova et al. (2006), the mixed-methods sequential explanatory design focuses on explanation and understanding through distinct quantitative and qualitative data collection and analysis phases. According to Venkatesh et al. (2013), this mixed-methods design is instrumental in offering a richer and more meaningful understanding of the issues under investigation by combining quantitative and qualitative data. In this context, the quantitative phase offers statistical evidence, while the qualitative phase develops an in-depth exploration, contextualisation, and explanations behind the findings. Fielding (2012) suggests that mixed methods allow triangulation of data from findings in the sequential phases that allow comparison and integration that enhances the credibility and validity of the findings. According to Polit and Beck (2010), the quantitative and qualitative research approaches contribute to the robustness of the research that fosters practical implications based on a thorough understanding. From these insights, the rationale for adopting the mixed method approach in the current study is to address the multifaceted nature of IS to develop a more comprehensive and in-depth understanding of the systems and users, allowing meaningful contributions to theory, practice, and policy in the field.

4.2 Research Design

In any research study, the research design is essential for a comprehensive perspective of the research framework. The research design involves a series of stages made by the researcher that establish the strategic decisions made in addressing the research problem, questions, and objectives (Carcary, 2009). Figure 4.1 represents the research design and stages to achieve the study's main objectives. The current study was accomplished based on the mixed methods design. According to Kerrigan (2014), the mixed methods design alludes to using qualitative and quantitative data collection and analysis approaches and comparing or relating the insights gathered from each approach to better understand the issues under investigation. New knowledge emerges in the interpretation and discussion of the areas of convergence or divergence experienced in the qualitative and quantitative results (Abdalla et al., 2018). Othman et al. (2020) suggest that the mixed method sequential explanatory research design facilitates the development of comprehensive analysis using mixed methods from diverse qualitative and quantitative data. This design enables the researcher to capture the richness of research aspects through qualitative methods while obtaining numerical data for statistical analysis necessary for quality, credibility, and reliability (Asenahabi, 2019). Researchers using this research design prioritise the methods equally, although the data analysis is independent. The results are integrated to develop an overall interpretation based on the convergence approach.

The sequential quantitative and qualitative design is systematically employed through a sequential approach, where the initial quantitative phase entails generating and testing the research hypotheses and exploring the potential factors influencing the phenomenon under study (Harlap et al., 2016). The quantitative phase informs the qualitative phase, considering that the data collected allows the researchers to delve deeper into quantitative results. Although the sequential mixed method design requires the two research methods, the current study largely relied on the quantitative approach. According to Conboy et al. (2012), quantitative research is considered a stronger approach to developing new knowledge compared to qualitative methods due to the statistical analysis and generalisation that is not realised in qualitative studies. Based on the research model of the quantitative study, a qualitative method was conducted via Machine Learning (ML) techniques to provide deeper insights into the research factors.

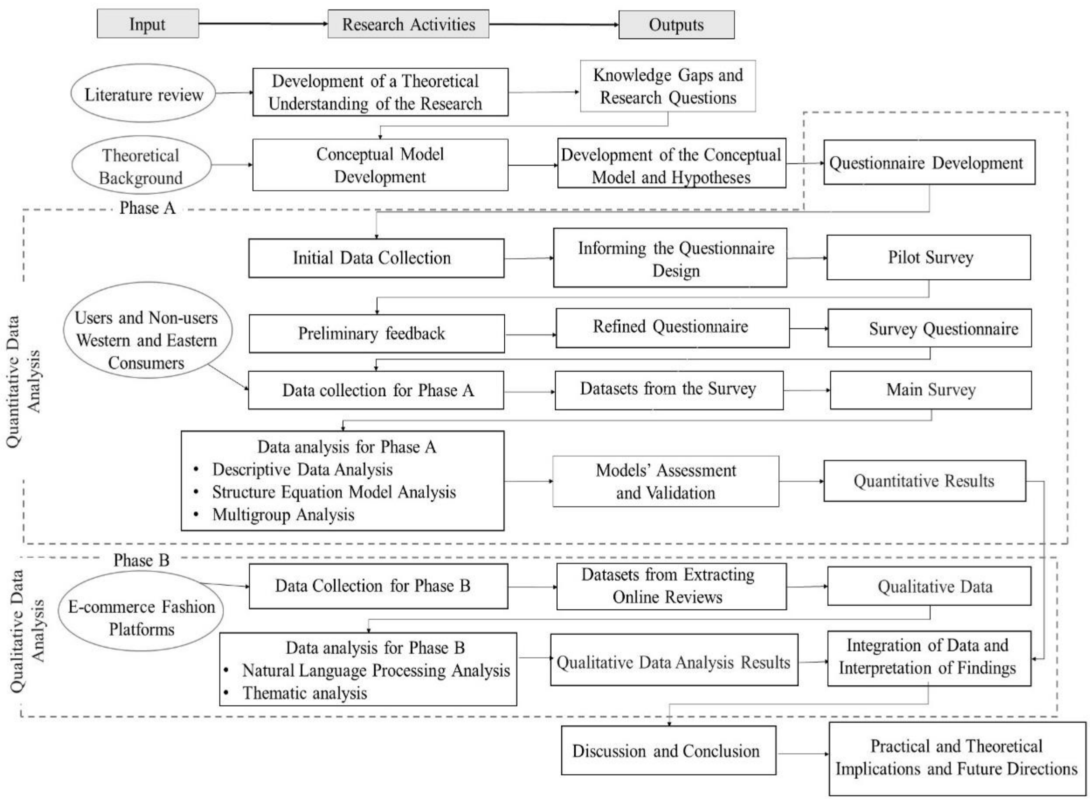

Figure 4.1. Research Design

This study adopted an explanatory research approach to address the main issues emerging in the research model. It facilitated the generation of findings highlighting the importance of 'What is happening?' or 'What is the impact? The approach helped to discover the cause-and-effect relationships in different variables of the phenomenon under investigation (Bryman &

Bell, 2015). This study was accomplished in three stages. The first was conducting a literature review to get a broad perspective on AI assistants and cultural theories with their application for different domains. The second stage was completing the quantitative method, which involved conducting the pilot study and the primary survey. The third stage was an ML study, which involved analysing reviews by online customers. The positivist research philosophy guided the quantitative phase of the study, while the interpretivist research philosophy was adopted for the qualitative phase. The positivist research philosophy fosters the use of quantitative methods that offer empirical evidence on the phenomenon under investigation. The interpretivism research philosophy suggests that reality is a social construct and knowledge can be developed from the experiences of different subjects (Holden & Lynch, 2004).

Firstly, a literature review was conducted to build a theoretical background and identify the knowledge gap that guided us in developing the research questions. A conceptual model was generated to demonstrate the research questions premised on the insights emerging from the interpretation of literature sources. Using the mixed method sequential explanatory research design, the quantitative phase was applied, followed by the qualitative research, which entailed collecting data that could contribute to a more nuanced interpretation of the research outcomes and provide context-specific understanding.

A quantitative survey was employed for data collection in the quantitative phase. According to Fakis et al. (2014), surveys are adequate in practically examining research models and hypotheses because they facilitate the collection of large volumes of data on the issues under investigation. The deductive approach was instrumental in the quantitative analysis when testing the research model regarding the customers' intention to use AI assistants in e-commerce. In this light, the literature review on cultural factors and AI assistant platforms highlighted the customers' attitudes and intentions to use this type of AI assistant for e-commerce. Chalmers (1990) suggested employing a deductive approach facilitates the development of a logical conclusion from the insights emerging in testing the hypotheses developed in the study. The proposed hypotheses focused on the pertinent theoretical aspects emerging from the information systems and marketing literature. Chapter 2 and Chapter 3 present the literature review and conceptual framework that was developed through a deduction process.

An analysis of online reviews was conducted to focus on the customers' use of e-commerce platforms. The ML method was included in this context because the research objective was to explore this phenomenon in-depth (Bryman & Bell, 2015). Subsequently, a theoretical model was established to demonstrate the relationships between the various concepts and variables from the literature review that were empirically assessed. As a result, the theoretical model was developed to address intention and consumer behaviour using AI assistants in Chapter 3. The findings of this research contribute to the current knowledge in the area of AI assistants and interdisciplinary research within culture, providing new opportunities for future research.

4.3 Justification of Research Method Design

As stated earlier, this study applies a mixed methods research strategy described by Ivankova (2006) using sequential quantitative and qualitative techniques. A mixed-method research design is a process for collecting, analysing, and mixing both qualitative and quantitative methods in a particular study to understand a single research problem (Ivankova, 2006). Quantitative data using survey questionnaires have been used primarily to collect numerical data to test and validate the research conceptual model. More precisely, quantitative data has been utilised to develop an initial understanding of the relationship between factors that influence e-commerce consumer attitudes and intentions. However, online reviews using qualitative data have been used to identify themes for designing AI assistants that reflect the key influencing factors on attitudes and intentions towards using AI assistants. Additionally, natural language processing techniques are utilised to clarify and explore the aspects of the prethemes that reflect associated variables. The advantages of using a mixed-method approach have been clearly shown in the information systems literature (Petter & Gallivan, 2004). This study adopts a mixed-method approach based on the following arguments: According to Kaplan and Duchon (1988), gathering various types of data using different methods and from different sources enhances the researchers' capacity to capture a broader perspective of the research problem, which leads to the better contextual basis of interpreting and validating the findings; Greene et al. (1989) suggest that a mixed method approach fosters stronger conclusions because the different research approaches complement and confirm each other. Considering the limited research on consumer culture in AI technologies in e-commerce, a mixed-method approach has been adopted to provide more details about consumers' knowledge, experience, and adoptions.

4.4 Quantitative Study Approach Overview

Quantitative research was done to evaluate the proposed conceptual model and the critical relationships among its constructs. This was accomplished by employing various statistical and analytic approaches in interpreting the data collected from the online survey. A multivariate data analysis was used to evaluate the relationships in the model. According to Hair et al. (2013), correlation analysis is used to establish the dependence among two or more factors that generate results. This analysis focused on how and the degree to which one of the factors associates with another (Cavana et al., 2001). An analysis using the Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to highlight the complex cause-effect relationships emerging in the model.

4.4.1 Measurement Design

Surveys are often used in quantitative studies to present research participants with structured questions that increase efficiency and accuracy in data collection. Therefore, quantitative data collected from surveys can be adequate in standardisation, making generalisations to a larger research population (Sidi et al., 2012). According to Kelley et al. (2003), quantitative survey data can be easily analysed using various statistical techniques to respond to the issues under investigation. Surveys are instrumental where investigations require high levels of confidentiality and anonymity and enhance the respondent's willingness to offer truthful information. They are also cost-effective to administer, unlike interviews requiring researchers' participation in the data collection process (Goertzen, 2017).

An online survey was administered to gather adequate data for testing the research hypotheses. The Qualtrics platform was used for designing the questionnaire and managing the collected data. The Qualtrics platform is a cloud-based tool used for creating and distributing surveys to the large online community. It allows users to collect data, analyse the results, and export the data in various formats. The questionnaire consisted of statements for each factor included in the conceptual model, as shown in Table 4.1, that required responses using a five-point Likert scale, ranging from 1 (strongly agree) to 5 (strongly disagree). Appendix A presents the questions for the factors in the survey questionnaire.

Table 4.1. Measurement Items

Factors	Code	Items	References
Perceived Usefulness	PU1	The AI assistant provides useful information.	Hsieh & Liao, 2011; Çelik & Yilmaz, 2011
	PU2	The AI assistant provides sufficient content.	
	PU3	The AI assistant makes it easy to find the content required.	
Perceived Ease of Use	PE1	Learning to use the AI assistant is easy for me.	Chung et al., 2020
	PE2	The interaction with the AI assistant is clear and understandable.	
	PE3	I would find it easy to use the AI assistant to search for what I want.	
Personalisation	PERS	If I changed to another brand, the products and services would not be as customised as I have now.	Chung et al., 2020
	PERS	The AI assistant offers products and services that would be difficult for me to find.	
	PERS	I feel that using the AI assistant and transacting with it may meet my personal needs.	

	PERS	The AI assistant provides information about products according to my preferences.	
Interactive Communication	ICOM	My interactions with the AI assistant can be more productive than face-to-face interactions with in-store personnel.	
	ICOM	Using AI assistants can be more efficient than other forms of communication.	
	ICOM	AI assistants can save a tremendous amount of time.	
Attitude	AT1	I would have positive feelings towards using the AI assistant.	Hassanein & Head, 2007
	AT2	The thought of browsing a product from the AI assistant is appealing to me.	
	AT3	It would be a good idea to find the right product using the AI assistant.	
Usage Intention	UI1	I will use the AI assistant regularly in the future.	Moon & Kim, 2001
	UI2	I will frequently use the AI assistant in the future.	
	UI3	I will strongly recommend others to use the AI assistant.	

The measurement scales considered that the adopted items were edited to fit the objectives of this study. Different studies have integrated measurement subscales to create a single measurement scale instead of using multiple separate scales, which enhanced their reliability (Polkosky & Lewis, 2003; Lewis & Hardzinski, 2015). However, this alternative has some limitations concerning internal reliability and construct validity. Therefore, the measurement scales for each construct were validated before the statistical analysis. The AI assistant interaction simulations were designed for performing most e-commerce functions, such as searching for information, recommending products, and contacting the brand. The survey consisted of two scenarios of AI assistant interaction to demonstrate variety in conversation outcomes. Appendix B presents the AI assistant interaction simulations. The measurement properties for the latent constructs and their indicators were calculated for construct reliability and internal consistency. The construct reliability and internal consistency were established using Cronbach alpha that was of a value higher than 0.7 (Bland & Altman, 1997). The average variance extracted values are higher than the value of 0.5. Therefore, the research instrument was adequate for data collection in this study.

4.4.2 Sample and Sampling Size

The target sample for this study was individuals who engage in e-commerce activities, regardless of whether they have used AI assistants or not. The goal was to investigate the usage intentions towards AI assistant adoption among users and non-users of AI assistants. The participants of this study were from various geographical locations, providing a cross-cultural perspective on the usage patterns of AI assistants in e-commerce. This was achieved using the sample from the professional survey platform Amazon Mechanical Turk (MTurk), assuming that its user base represents a diverse range of backgrounds and experiences. The inclusion criteria focused on ensuring the participants demonstrated prior experience with online shopping and e-commerce activities. The rationale behind this is to ensure that offered responses are relevant to the current study concerning interactions with AI assistants in e-commerce. Therefore, participants with no previous experience with AI assistants were engaged in this study based on the notion that their attitudes could be compared with those with such experience. This comparison aimed to identify the factors that drive their interest or lack of interest in using AI assistants in e-commerce. MTurk allows researchers to receive data with IP addresses to enhance the quality of the responses (Forkus et al., 2022). Then, the sample was divided into two groups during the data analysis: Eastern and Western groups were identified based on geolocation techniques of the IP addresses related to the responses (Burnette et al., 2022). Using two groups from different cultures (Western and Eastern) through the MTurk tool can be justified for several reasons. The MTurk platform helps researchers reach a diverse group of participants from different areas, making the study more interesting by showing how people from different cultures think and act differently (Keith et al., 2024). This makes the study more valid because it can apply to more cultures than just one (Hitchcock & Nastasi, 2024). MTurk also uses IP addresses and location techniques to accurately group people into Eastern and Western cultures, which helps researchers compare how cultural differences affect the study's results (Aguinis et al., 2012). This method helps find patterns and differences between cultures under AI assistants as a recent development technology. Finally, MTurk is efficient and cost-effective, making it easier to include people from different cultures in studies than other data collection methods (Keith et al., 2024). However, the grouping was premised on the assumption that the physical location of the individual aligned with the cultural characteristics associated with the region. Furthermore, the limitations in using internet services in some jurisdictions imply that some users might use VPNs and proxies that misrepresent their geographic location (Khan et al., 2023). Some users from different cultures might have migrated or travelled to their current physical places. Using the IP addresses also lacked a clear reflection on the subcultures among the two primary cultures that might substantially highlight differences in the use of advanced technologies. Therefore, data collection focused on engaging a diverse population to ensure that participants were representative of people from different regions. The main consideration for participation was the willingness to contribute to the current study by giving consent and answering screening questions about e-commerce activities and AI assistants. The diversity in the research sample enhanced the potential for generalisation to a broader audience and the practical application of the research findings.

For structure equation modelling, several analysts and experts adopted several rules of thumb in predicting sample sizes for investigations that utilise structural equation modelling as an analysis method. For instance, Hair et al. (2013) noticed that a sample size of 150-300 (6-10 indicators) is appropriate for critical structure equation modelling studies. For this study, the sample size was determined using the Australian Bureau of Statistics calculator, assuming that the population of e-commerce users is unknown. The parameters used for determining the sampling size are the following (Confidence level: 95% - Population Size: the option of the sampling size is left blank due to the population size being very large. The proportion has a value of 0.5 due to the unknown proportion, and it should be set to 0.5, as this produces a conservative variance estimate with a confidence interval of 0.05. Consequently, a sample size of 385 participants was selected for the current study. The two main factors affecting the sample size calculation were the P value and statistical power. The statistical P value for significance is 0.05, and the statistical power is generally between 80% and 95%, depending on the size of the research sample (Whitley & Ball, 2002). According to the Nomogram form for calculating power, the power of 400 and 385 sample size is 97%, achieving higher power for the testing validity and sampling size (Whitley & Ball, 2002). Therefore, 400 participants were recruited for this survey and after pre-processing the data, the participants included were 397.

4.4.3 Data Collection Method

The final survey was conducted in December 2021. At the beginning of the study, the participants had instructions regarding the definition of AI assistants, which helped to establish if they had such an experience or not. During the survey, they were shown two examples of AI assistant interaction simulations to help understand what websites or applications could be considered AI assistants in e-commerce. During the survey, participants were asked about their online purchasing history, their experiences with AI assistants and what information they needed to obtain from them. The survey was developed on the Qualtrics software, and a link was sent to the MTurk platform. The MTurk users shared the link to access the survey on the Qualtrics platform, where the data was automatically recorded and stored. MTurk is an online platform that facilitates crowdsourcing, making it easy for organisations and individuals to outsource tasks to a diverse and widely distributed workforce in a virtual working environment (Aguinis et al., 2021). The platform facilitates various tasks ranging from simple data validation tasks to more complex and subjective undertakings, such as participating in surveys and content moderation. The platform guarantees data accuracy by ensuring that participants can only engage once on a task (Aguinis et al., 2021). This enhances the quality of the data collected and contributes to the credibility and reliability of the application of the insights gathered. Additionally, the global reach of MTurk offers an opportunity to develop insights and applications that are relevant to a diverse population.

Additionally, the platform offers a strategic approach that reduces the costs and time required at each stage of collecting data (Ashfaq et al., 2020). This is attributed to the ease of gathering and annotating large volumes of data that are required in survey studies and the continuous iterations and corrections. As a sampling technique, Mturk is appropriate for empirical studies (Chandler & Shapiro, 2016). The application of this approach is premised on previous marketing and business studies in virtual assistants that used Mturk for their online survey (Kull & Monahan,2021; Ashfaq et al., 2020; Sheehan & Gottlieb, 2020; Go & Sundar, 2019; Araujo, 2018). Before conducting the main survey, a pre-testing was conducted to establish if the items were aligned with the issues of interest and to improve the quality of these questions. Pre-testing a questionnaire highlights problems that might emerge, compromising it in collecting primary data. It facilitates gathering preliminary insights to improve clarity, making it easy for the participants to complete the survey (Ghazi et al., 2018). The pilot study was conducted with 26 participants. The feedback from the participants helped in modifying the questionnaire, mainly on the inquiries related to the AI assistant usage and the participants' previous experiences.

4.4.4 Data Analysis Method

The data analysis approach was drawn from Hair et al. (2010). These are the primary techniques of multivariate analysis, which are multiple regressions and structural equation modelling. The various statistical analyses used Excel, IBM SPSS, and SmartPLS software. Several previous studies have used multivariate analysis techniques and the PLS-SEM to address more than one variable and analyse more than one statistical outcome (Sheehan & Gottlieb, 2020; Araujo, 2018). PLS-SEM is often implemented in marketing and social science research and is appropriate for studies that collect nonnormal data and can facilitate the use of any size of research sample (Hair et al., 2019). The PLS-SEM approach allows the validation of the hypothesis to establish if there is synchronous modelling of correlations experienced between the independent and dependent variables (Hair et al., 2013). The PLS-SEM was used to identify the relationships that exist among the independent and dependent variables. Additionally, a range of experimental and descriptive analysis procedures were used to assess the relationships between the influential constructs outlined in the theoretical model. Evaluating the correlations helped to predict the relationships, and multivariate techniques were employed to verify the relationships identified in the correlations (Hair et al., 2013).

Field (2009) suggests that statistical analysis of any kind should be done after checking for missing data. Also, normal distribution is necessary to ensure that the data is adequate for credible and reliable results. The risk of missing data was mitigated by leveraging the features of the Qualtrics platform in conducting online surveys that prevent incomplete submissions. The 5-point Likert scale was used to record the survey responses, followed by transforming the categorical data via SPSS to test the collected data's normality. After testing the normality of the data survey, the Spearman correlation approach and multiple regression analysis were used for the correlation test because the collected data are non-normality distribution, and the model included various constructs. Measurement scale analysis was part of PLS-SEM strategies to establish the meanings associated with variables in the model by assessing the reliability and validity of the scale. Cronbach's alpha, the composite reliability, and the average variance extracted tests were used to assess the scale's reliability and validity. The analysis to confirm the measurement model was coupled by establishing the relationships between the variables emerging in the hypothetical structural model and the latent variables. After testing measurement scales to establish reliability and validity, the conceptual model and path coefficients were assessed to test the significance of the hypotheses. To investigate the relationships of the research model, the PLS-SEM was employed for path analysis (Hair et al., 2019).

4.5 Qualitative Study Approach Overview

This section is about the qualitative study that applied ML and natural language processing techniques for collecting and analysing online reviews. The Latent Dirichlet allocation (LDA) model is the most used topic model for analysing online reviews (Sutherland et al., 2020). The LDA model was used as a relative topic model to extract the common topics and explore deep insights to support the outcome of the quantitative study. The thematic analysis was further conducted to synthesise and comprehend each topic's themes of the LDA model. Therefore, online reviews of e-commerce tools (website and mobile applications) were collected to provide valuable insights for the AI assistant designs and support the findings of the quantitative study.

4.5.1 Data Collection Method

Data collected focused on online consumer reviews, which, according to Xie et al. (2014), are critical sources of insights into consumer decision-making processes. Amblee and Bui (2011) suggest that online consumer reviews offer social proof concerning the perceptions and behaviours that emerge among people using a product or service. Suggestively, they enhance transparency and accountability in research by including the consumers' perspective about the products and services (Zhang et al., 2014). Therefore, focusing on online consumer reviews offered an opportunity to enhance the quality of the current study and its contribution to theory and practice. The online reviews of technology products of the Louis Vuitton brand were collected as a case study in the fashion industry e-commerce. The current virtual assistants used by Louis Vuitton have limited geographic locations, and the CEO of Louis Vuitton is planning to develop virtual assistants to increase their available locations and platforms (Arthur, 2017). Understanding consumers' needs and challenges towards the existing online communication tools in e-commerce could support developers in enhancing the design of virtual assistants. Therefore, this study aimed to analyse the reviews of the current technologies of Louis Vuitton to provide practical conclusions for how the brand can enhance its virtual assistants.

For this study, the data was collected from three platforms: Trustpilot, Apple App Store, and Google Play app store review platforms. Trustpilot is a well-known technology review site. It is a digital platform connecting companies and customers to build trust and encourage cooperation. Trustpilot facilitates feedback that can help customers make confident decisions when purchasing and provides substantial insights for companies that can be used to improve customer experiences. Apple App Store and Google Play allow users to review applications that highlight their experiences using the technical aspects of what is offered. Therefore, a web scraper code was developed in Python language for collecting the reviews of the online e-commerce applications of Louis Vuitton. Web scraping is an intuitive way of extracting vast data from sites that are unorganised and scattered. Web scraping assists in collecting unstructured data and storing it in an organised format. The methods for scraping webpages, including internet services, APIs, and developing specialised programs. Therefore, the code was programmed by adopting existing libraries of Python programming language to develop this study's reviews scraper. The total collected data was 996, including three attributes: date, review, rank, and description.

4.5.2 Data Pre-processing

The pre-processing technique was conducted to clean the data before the data analysis (Famili et al., 1997). Pre-processing entails cleaning raw data to make it usable and transform it into intelligible formats. Raw or actual data is often inadequately formatted; it can be incomplete and can be compromised by human errors. Data pre-processing resolves these challenges, making the datasets more adequate for analysis. Therefore, the data pre-processing step was conducted twice to improve this study's results. The review pre-processing is an important step that can influence the success of ML and data mining projects. It speeds up data analysis from datasets and can eventually impact the efficiency of ML frameworks.

The first step of review pre-processing was changing the case or letter format. Changing the case entails transforming the texts to lowercase or uppercase so that the word strings are consistent. Lowercasing is the most common choice in NLP analysis. A lower method was used for this analysis to convert all review texts to lowercase. The lower method is a Python function that converts strings to lowercase. Lowercasing is critical for generating a single token of lowercase and uppercase variants of the same word (Ferrario & Nagelin, 2020). The next step was removing emoticons, pictographs, transport, and map symbols from the reviews. This step was essential to remove any non-text object from the reviews. The regular expression model with a compiled method was used to specify a set of patterns matching the required removed forms. The next step was removing punctuation marks and digits from using the natural language toolkit Python library. Then, removing extra spaces and multiple lines methods were used as the next pre-processing step for cleaning the collected reviews. Strip in Python was applied to delete the additional lines. "Stop-words" are the frequent words used in sentence construction. Examples of stop-words in English are the, are, of, in, and. For NLP applications, such as sentiment analysis, document categorisation, and spam filtering, the stop-words are removed at the pre-processing stage because they are redundant (Sarica & Luo, 2021). Therefore, the second time of pre-processing, a method of removing stop words was added to improve the results. The Natural Language Toolkit (NLTK) library is a standard Python library offering various algorithms for NLP. The up-to-date packages were downloaded from the NLTK library to remove the stop words. The following section is about data annotation and vectorisation, which are essential steps for NLP analysis.

4.5.3 Data Annotation and Vectorisation

The collected reviews were classified negatively and positively based on provided ratings and the sentiment analyser's outcomes. The ratings of numbers 1, 2, and 3 referred to negative reviews, and 4 and 5 referred to positive reviews. The collected reviews included 533 negative and 454 positive reviews. The sentiment analyser-based classification introduced 105 negative reviews and 233 positive reviews. The data annotation techniques were applied to make text identifiable to system text recognition to develop such datasets. The data vectorisation method was applied after data annotation, as it was required for the NLP analysis, such as keywords extractions and topic modelling algorithms (Hasan et al., 2019). Data vectorisation refers to the practice of transforming words into digits. It is a technique in NLP that maps phrases and words from a lexicon to a matching vector of real numbers.

4.5.4 Data Analysis Method

The NLP analysis was used to understand how systems analyse a document's content, subtleties, and emotions. NLP was adequate because it could precisely extract the data and insights included within the document and then arrange them into the appropriate categories. The NLP techniques used in this study entailed a method to address the research questions and for keyword extraction from collected reviews. Keyword extraction provides a straightforward and adaptable method for extracting top-frequency words from documents. The Frequency Inverse Document Frequency (TF-IDF) model was adopted to identify the most frequently occurring words in the collected reviews. The TF-IDF model could assign more excellent relevance ratings to words appearing in fewer corpus documents. The TF-IDF compares a word's frequency in a document to its overall frequency within-corpus. The next step was identifying the most frequent of the three-word combinations and the most frequent of the top words using the TF-IDF model for the negative and positive collected reviews. Then, the produced data visualisations consisted of plot bars and word clouds representing negative and positive reviews. A cloud of words is also a text representation technique that defines the appearance of words in a document.

A topics model was conducted for this study to capture the critical topics of the current communication tools in e-commerce that matter to consumers. AI-powered text analysis employs a broad range of approaches or techniques to interpret language naturally; topic modelling is one of them (Nikolenko et al., 2017). Topic modelling is an ML approach that automatically evaluates text data to discover a cluster of words from documents (Maier et al., 2018). Topic modelling was conducted to understand what consumers say about certain aspects of the current communication tools. The collected reviews included for analysis were 987 rows with 235892 words. The collected reviews had twenty topics, with ten passes found via the topic modelling for better-displaying topics.

After the topic modelling method, the thematic analysis was applied to capture the theme of each topic of this study. Thematic analysis is a qualitative strategy that entails familiarising with the dataset to establish, evaluate, and report on patterns and themes (Kiger & Varpio, 2020). In this context, the deductive thematic analysis was conducted to find the pre-defined themes based on the main variables of the research model in the quantitative study.

4.6 Integration of Data and Interpretation of Findings

The application of the mixed methods started with quantitative data collection and analysis and built to qualitative data collection and analysis, which led to the interpretation. The quantitative results were used as a new instrument for the qualitative strand. The rationale for conducting the mixed method design allows for a comprehensive interpretation of the research topic by triangulating quantitative and qualitative data. This design enables the researcher to capture the richness of research aspects through qualitative methods while obtaining numerical data for statistical analysis (Asenahabi, 2019). The design of this method facilitates a sequential approach, where the initial quantitative phase helps generate hypotheses and explore potential factors influencing the phenomenon under study. This quantitative exploration informs the subsequent qualitative phase, allowing for the validation and complement of findings. Furthermore, the sequential mixed methods design enables the researcher to dig deeper into quantitative results. Therefore, the qualitative data were collected to interpret the research outcomes better and provide context-specific understanding (Subedi, 2016).

The integrated quantitative and qualitative methods are intrinsically linked and mutually illuminating, thereby creating a comprehensive understanding of issues under investigation (Woolley, 2009). In mixed methods research, integration between two methods refers to the specific relationship between these methods that retain their paradigmatic elements, although they are aligned in pursuing the shared objective of improving and creating new knowledge (Guetterman et al., 2018). Mixed methods foster the integration of findings and connection of the two methods to develop meta-inferences that create a better understanding (Ivankova et al., 2006) and more insights concerning a particular phenomenon from different perspectives (Shannon-Baker, 2016). Consequently, mixed-method research outcomes can be unhelpful if there is a failure to link, connect, or integrate the quantitative and qualitative insights (Moran-Ellis et al., 2006). The concept of mixing methods extends beyond using two or more research methods in the same study. Uprichard and Dawney (2019) argue that data integration must lie in the extent to which data is interpreted from different sources meaningfully. Suggestively, there are three stages where integration can be experienced in a mixed methods study– design, methods, and interpretation and reporting (Fetters et al., 2013).

In the current study, there was no integration at the design level because a sequential mixed methods design was adopted whereby the quantitative phase was conducted first and informed the qualitative phase. However, the merging approach was adopted, which entails comparing and interpreting the qualitative and quantitative results and establishing how the insights from each method complement the other. Data merging is carried out following the quantitative statistical analysis and an analysis of the qualitative data (Jantsch & Neves, 2022). Deductive thematic analysis was employed premised on predetermined codes for the qualitative data. This approach ensured that the qualitative data was aligned with the key constructs measured in the quantitative phase, which increased efficiency in merging the data sets. Data integration in the narrative can follow many approaches, such as weaving, contiguous, or staged approaches (Fetters et al., 2013). The contiguous narrative approach was adopted, which entailed presenting and separating the narrative for the quantitative and qualitative findings in Chapters 5 and 6, respectively. However, the insights from both approaches were later merged in Chapter 6.

4.7 Ethics of the Research

This research involves human participants for data collection. To ensure the anonymity and ethical protection of the participants, the Human Research Ethics Committee (HREC) – at the University of Technology Sydney approved the ethical form along with the protocol number approval, ETH 20-5011.

4.8 Chapter Summary

This chapter discusses the overview of the research methodology adopted in the current investigation to test the proposed conceptual model concerning AI assistant applications in e-commerce. This chapter addresses the research methodology, the research approach, and the relevant analytical techniques used. The study was accomplished using a mixed-method design that integrates quantitative and qualitative approaches, including machine-learning research approaches. The approach began with a review of relevant literature sources and establishing logical relationships between different variables. This was followed by a quantitative phase that offered further insights using empirical evidence. Following the quantitative phase, the ML approach provided deep insights into the identified constructs of the research model. The quantitative data set analysis involved various statistical techniques that include primary descriptive analyses, multivariate and correlation techniques, and PLS-SEM using Excel, IBM SPSS and Smart PLS (Version 4) software. The analysis allowed testing of the conceptual model and hypotheses to develop the final empirical model, highlighting the interrelationships emerging among the different variables. The second phase involved an ML approach for analysing the reviews of e-commerce applications of the fashion brand Louis Vuitton. The following chapter addresses the data analysis of the quantitative phase.

Chapter 5. Quantitative Data Analysis and Results

The primary research objective centred on exploring users' perspectives on the intention to use AI assistants in e-commerce. Following the initial data analysis, the conceptual model's representation was formulated. A pivotal aspect of the conceptual model involves the application of the Technology Acceptance Model within the context of AI shopping assistants. This model clarifies the connections between the adoption of AI assistants among both users and non-users of online shoppers. Quantitative data analysis was conducted to test the proposed research model. The quantitative data analysis includes two parts: first, examining the appropriateness of the collected data in terms of validity and reliability to ensure the construct validation is satisfactory; second, testing the hypotheses on the relationships between the research constructs. Therefore, this chapter presents several summarised tables and figures describing the findings of the quantitative data analysis.

Initiating with a descriptive analysis of the survey and the demographic data of respondents, this chapter progresses to undertake data cleaning, testing, and validation for normality and effective representation. The subsequent stages involve the application of the structural equations modeling procedure, the development of the conceptual model, and the formulation of hypotheses. Following these steps, the process includes data screening, conducting validity checks for the final structural model, and an investigation into the effects. In the end, multigroup analysis was presented for testing the model related to cross-culture investigation.

5.1 Questionnaire Survey and Participants Demographics

As described in Methodology Chapter 4, a survey instrument was developed to examine the factors influencing online consumer attitudes and intention to engage with AI assistants in e-commerce. The survey questionnaire contained four constructs and two internal factors with nineteen items. The five-point Likert scale was used for the survey instrument. The following sections describe the survey and the participants' profiles.

5.1.1 Questionnaire Survey

A questionnaire survey was conducted online, filled out by individuals with experience with e-commerce and online shopping. The survey was conducted on the most popular data collection platform, MTurk, among scholars (Kull & Monahan, 2021; Ashfaq et al., 2020). According to Hitlin (2016), most users of MTurk reside in different regions around the world. Participants in this study came from various age groups, educational levels, cultural backgrounds, online purchase habits, and experience statuses with AI assistants. The type of questionnaire was a self-administered questionnaire using the Qualtrics platform. The self-administered questionnaire is more efficient than the interviewer-administered questionnaire in terms of no possibility of interviewer bias (Sakshaug et al., 2017).

The validated measurement scales of this study are adopted from prior literature to ensure the reliability and validity of the survey items, as indicated in the methodology Chapter 4. These items were adapted and edited to fit the objectives of this study. Respondents were required to fill out the questionnaire that included both open-ended and closed-ended questions. The questionnaire included items to measure all factors used in the conceptual research model. Consistent with the literature on measurement scale development (Polkosky & Lewis, 2003; Lewis & Hardzinski, 2015), the measurement scale is tested for internal reliability and construct validity, as shown in Table 5.19. In total, 400 participants completed the survey (more details on the data collection procedure in Chapter 4). After removing incomplete responses, a total of 397 responses remained for data analysis. The following section describes the respondents' profiles of the survey.

5.1.2 Demographic Characteristics of Respondents

The demographic profile of the participants is presented in the subsequent table.

Table 5.1. Demographic Profile of Respondents.

Demographic	Characteristics	Frequency (n)	Percentage (%)
Gender	Female	153	39
	Male	244	61
Culture	Western	293	74
	Eastern	104	26
Age (yrs.)	18 - 25	22	5.54
	25 - 35	209	52.64
	35 - 45	98	24.69
	45 - 55	46	11.59
	55 - 65	15	3.78
	Greater than 65	7	1.76
Degree	Bachelor's degree	262	65.99
	Master's degree	84	21.16
	High School Degree	42	10.58
	Doctorate Degree	7	1.76
	Certificate IV and associates	2	0.50
Income	$150,000 or more	4	1.01
	Less than $10,000	37	9.32
	$80,000 to 150,000	74	18.64
	$10,000 to $40,000	110	27.71
	$40,000 to $80,000	172	43.32
Prior experience using AI assistants	Users	312	78.59
	Non-users	85	21.41
The habit of purchasing a good online	3-6 months ago.	135	34.01
	Within the last three months.	118	29.72
	6-12 months ago.	104	26.20
	More than a year ago.	28	7.05

From Table 5.1., it can be observed that the gender distribution breakdown among the respondents indicates that 61% identified as male, while 39% identified as female. This gender distribution demonstrates a slight majority of male participants in the study and is consistent with the average of people who use AI chatbot technologies (Said et al., 2022; Chen et al., 2021). Figure 5.1 illustrates the presentation of these results.

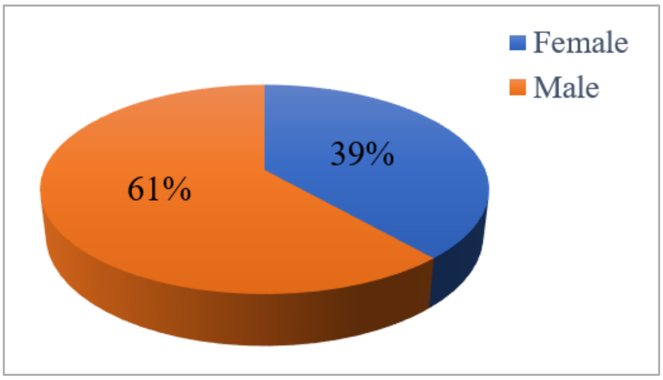

Figure 5.1. Gender of participants

Considering the cultural background of respondents, the respondents were divided into two cultures (Western and Eastern) based on the geo-location's technology (IP address). The responses' geo-locations were identified in eleven countries. The location of each country was classified into either Western or Eastern cultures. The total number of Western respondents was 293, and the respondents were from the cultures of the United States of America, the United Kingdom, Brazil, Australia, Italy, and France. In contrast, the total number of Eastern respondents is 104, and the respondents were from the cultures of India, China, Bangladesh, Azerbaijan, and Turkey. This classification was performed with the acknowledgment that several other countries can be added to each group (Hofstede, 1983). This distribution shows that the growing use of online shopping and AI agents is a worldwide phenomenon. While the growth varies unevenly from country to country, the Western respondents were a significant majority of the respondents. This distribution is consistent with previous studies that found consumers from an individualistic culture (Western) are more likely to use the Internet for e-commerce than those from a collectivistic culture (Eastern) (Zhou et al., 2017; Hofstede, 2011). Furthermore, Table 5.1 provides the age distribution of the respondents. The data reveals that the age group with the most respondents was 25-45, accounting for 77.3%. This age range is particularly significant as it represents the prime demographic for the online shopper group (Fokina, 2022). The high representation of respondents from this age group suggests that the study sample effectively captured individuals most likely to engage with e-commerce channels.

The next age group regarding respondents' representation was above 45, comprising 15.3% of the total, and 5% of the participants fell within the 18-25 age range. This finding indicates the inclusion of participants from a slightly older demographic, demonstrating a diverse age distribution within the study sample.

Moreover, 65.9% of respondents possess a bachelor's degree, with 22.92% holding a postgraduate degree and 10.58% having a high school degree. When comparing these proportions to the educated population aged 25 to 45, participants in this study exhibit higher educational levels. Additionally, individuals with high school degrees have a relatively minor representation in the sample compared to global statistics (2021). This indicates that individuals knowledgeable about AI technologies tend to be well-educated compared to the international population. Figure 5.2 provides a visual representation of these results.

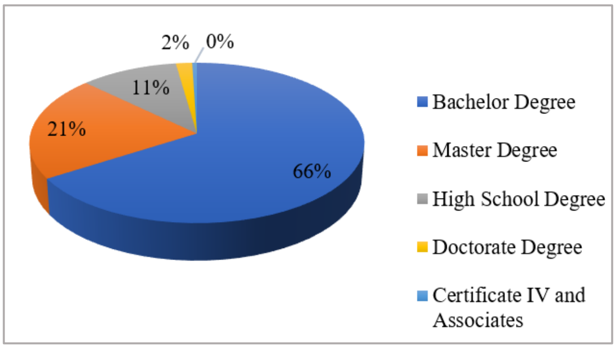

Figure 5.2. Education level of the participants

In terms of annual household income, 43.3% of respondents reported an annual household income range of $40,000 to $80,000, 27.7% of the respondents have an annual household income range of $10,000 to $40,000, and 18.6% of the respondents reported an annual household income range of $80,001 to $150,000. The percentage of respondents engaging in online shopping aligns with the average observed among experienced online purchasers (Hernández et al., 2011). Regarding AI assistants, 79% of respondents had utilised an AI assistant. This high percentage indicates that the participants have the necessary experience and familiarity with AI assistants, positioning them as potential users of AI assistants as an e-commerce tool. Figure 5.3 highlights the participants' interest in obtaining specific information or services from AI assistants. The most prominent area of interest reported by the respondents was obtaining the product's price, with 136 respondents (44%) expressing their interest in this aspect. Following closely, 118 respondents (38%) indicated an interest in product-related information, while 24 respondents (8%) expressed interest in promotions. These findings demonstrate the specific focus areas for participants when engaging with an AI assistant, providing valuable insights into their preferences and requirements. Table 5.2 presents the reasons provided by respondents for not interacting with the AI assistant.

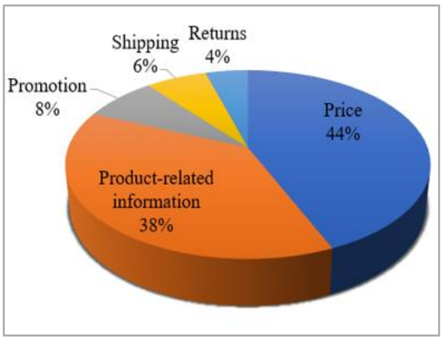

Figure 5.3. Information Obtained from AI Assistants

Table 5.2. Reasons for Not Using AI Assistants by Respondents

Reasons	Frequency	Percentage
I prefer interaction with human agents.	38	45
I could not find the chat label easily.	13	15
I would need to spend too much time interacting with the AI assistants.	9	11
I feel AI assistants do not match their search preferences.	8	9
I did not need any help	7	8
I am not familiar with AI assistants.	5	6
There was no AI assistant.	3	4
I feel AI assistants do not match their purchase preferences.	2	2

The top three reasons reported were a preference for human agents (45%), difficulty in locating the chat label quickly (15%), and the need to spend too much time interacting with the AI assistant (11%). These findings reflect the respondents' inclination towards human interaction and suggest that the AI assistants' ability to provide human-like responses could cater to the preferences of participants who desire to interact with human agents. This aligns with previous research (Gnewuch et al., 2018; Hill et al., 2015) that emphasises the importance of human-like responses in AI assistants to address customer preferences. These findings shed light on the participants' usage patterns, preferences, and experiences with AI assistants. The high percentage of respondents who had used AI assistants demonstrates their familiarity with such technology, positioning them as potential users of AI assistants in an e-commerce context. In terms of purchasing behaviour and the recent product purchase timeframe, 34% of the respondent's total had purchased products within the last 3-6 months, 29.7% of the respondents purchased a product within the last three months, 26.2% of the respondents reported their most recent product purchase occurring 6-12 months ago and 7% of them reported making their most recent product purchase over a year ago.

5.2 Data Examination

Before conducting PLS-SEM, a data examination was performed, encompassing multiple essential steps. This examination included the elimination of missing records, representation of answers, assessment of the variance of variables within constructs, and evaluation of construct reliability and validity. This crucial process is essential as it ensures that the data is appropriately prepared for model construction (Berger & Zhou, 2014). Since modelling methods often have specific assumptions that data must adhere to, a thorough data examination becomes imperative to verify whether these requirements are met. Through this step, it can be determined if the data satisfies all the necessary requirements for PLS-SEM, enabling the establishment of sets of constructs, each comprising a specific number of variables. Hence, facilitating the formation of a set of constructs, each comprising a specific number of variables.

5.2.1 Missing Data Analysis

To successfully evaluate data, data must first be observed for missing values (Chhabra et al., 2017). However, as outlined in Section 5.1.1, all missing data were eliminated for this study before additional analyses. Table 5.3 to Table 5.6 presents the responses of the primary constructs of this study. The missing data analysis was performed using descriptive statistics, as shown in the descriptive analysis results for each construct (Table 5.7 to Table 5.12). In this phase, the study excluded rows with missing data, specifically in cases where more than two constructs and their corresponding items were left unanswered.

Table 5.3. Responses of Perceived Usefulness and Ease of Use

Perceived usefulness and ease of use		5-point Likert scale					
Item	Statement	5	4	3	2	1	Total
PU1	The AI assistant provides useful information.	85	225	68	13	6	397
PU2	The AI assistant provides sufficient content.	123	168	76	26	4	397
PU3	The AI assistant makes it easy to find the content required.	102	197	70	11	17	397
PE1	Learning to use the AI assistant is easy for me.	105	216	64	7	5	397
PE2	The interaction with the AI assistant is clear and understandable.	146	164	58	26	3	397
PE3	I would find it easy to use the AI assistant to search for what I want.	110	211	54	12	10	397

Table 5.3 shows responses on a 5-point Likert scale for perceived usefulness and perceived ease of use (PU1, PU2, PUE, PE1, PE2, and PE3) with 397 participants. Most participants rated high (5) and (4) as strongly agree and agree' responses for usefulness and ease of use, indicating positive views of the AI assistants.

Table 5.4. Responses of AI Assistant Capabilities

Personalisation and Interactive Communication		5-point Likert scale					
Item	Statement	5	4	3	2	1	Total
PER1	If I changed to another brand, the products and services would not be as customised as I have now.	62	187	107	32	9	397
PER2	The AI assistant offers products and services that would be difficult for me to find.	86	158	80	57	16	397
PER3	I feel that using the AI assistant and transacting with it may meet my personal needs.	73	197	99	17	11	397
PER 4	The AI assistant provides information about products according to my preferences.	97	192	88	17	3	397
IC1	My interactions with the AI assistant can be more productive than face-to-face interactions with in-store personnel.	55	200	101	29	12	397
IC2	Using AI assistants can be more efficient than other forms of communication.	97	165	94	34	7	397
IC3	AI assistants can save a tremendous amount of time.	93	203	73	16	12	397

The same can be observed from Table 5.4, which shows 397 participants' 5-point Likert scale responses for personalisation and interactive communication (PER1-4, IC1-3). Most participants provided high ratings (5) and (4), indicating favourable perceptions of the AI assistant's capabilities.

Table 5.5. Responses of Attitude towards the Use

Attitude		5-point Likert scale					
Item	Statement	5	4	3	2	1	Total
AT1	I would have positive feelings towards using the AI assistant.	81	203	90	15	8	397
AT2	The thought of browsing a product from the AI assistant is appealing to me.	109	168	78	32	10	397
AT3	It would be a good idea to find the right product using the AI assistant.	95	205	64	18	15	397

Table 5.5 displays the responses of 397 participants on a 5-point Likert scale, expressing their attitude towards utilising the AI virtual assistant (AT1, AT2, and AT3). A significant majority

assigned high ratings (5) and (4), revealing their positive views of the AI assistant's capabilities and potential.

Table 5.6. Responses of Usage Intention

Usage Intention		5-point Likert scale					
Item	Statement	5	4	3	2	1	Total
UI1	I will use the AI assistant regularly in the future.	71	206	92	22	6	397
UI2	I will frequently use the AI assistant in the future.	115	167	73	36	6	397
UI3	I will strongly recommend others to use the AI assistant.	104	178	76	23	16	397

A significant majority of the participants' responses were on a scale for usage intention (UI1, U1, and U3) with high ratings (5) and (4), suggesting a strong intention to use the AI assistant regularly and frequently in the future. Also, many participants expressed a willingness to recommend others to use the AI assistant, reflecting a positive belief in its potential benefits.

5.2.2 Descriptive Data Analysis

Table 5.7 to Table 5.12 demonstrate the descriptive statistics for each construct of the survey study separately. Descriptive statistics include two essential factors: standard deviations and standard errors of the mean. The standard deviation (SD) indicates how accurate the average value of the collected data was. Nevertheless, the standard error of the mean (SE) helps determine how accurately a particular sample reflects the population (Dubois et al., 2015). The SD and SE values are small across all the tested constructs of this study. Thus, the sample can be considered a reliable reflection of the population.

Table 5.7. Descriptive Statistics for Perceived Usefulness

VAR	N	Mean		SD	Variance	Skewness		Kurtosis	
	Statistic	Statistic	SE	Statistic	Statistic	Statistic	SE	Statistic	SE
PU1	397	3.93	0.040	0.806	0.649	-0.953	0.122	1.758	0.244
PU2	397	3.96	0.046	0.924	0.854	-0.725	0.122	0.128	0.244
PU3	397	3.90	0.048	0.960	0.921	-1.153	0.122	1.618	0.244

The descriptive analysis results are essential for observing the actual variance values, which help depict the homogeneity of variables within factors. Table 5.7 displays the mean, standard error, and standard deviation for the perceived usefulness construct, which is assessed using three questions. The mean values for each question are consistently above 3, signifying that, on average, participants express agreement regarding the helpfulness of using AI assistants. Particularly, participants tend to mostly agree that utilizing AI assistants provides useful information (mean=3.93, SD=0.806). Additionally, the table indicates that skewness scores fall between -0.5 and -1, and kurtosis scores are less than three, suggesting deviations from a normal distribution.

Table 5.8. Descriptive Statistics for Perceived Ease of Use

VAR	N	Mean		SD	Variance	Skewness		Kurtosis	
	Statistic	Statistic	SE	Statistic	Statistic	Statistic	SE	Statistic	SE
PE1	397	4.03	0.039	0.781	0.610	-0.915	0.122	1.835	0.244
PE2	397	4.07	0.046	0.917	0.841	-0.885	0.122	0.335	0.244
PE3	397	4.01	0.044	0.873	0.763	-1.199	0.122	2.145	0.244

The mean scores for PE1, PE2, and PE3 are 4.03, 4.07, and 4.01, respectively, as shown in Table 5.8, indicating that, on average, participants perceive the AI assistant to be easy to use. The standard deviations (SD) for PE1, PE2, and PE3 are 0.039, 0.046, and 0.044, respectively, which suggest relatively low variability in responses. Skewness values ranging from -0.915 to -1.199 and Kurtosis values below three suggest that the variables show non-normal distribution.

Table 5.9. Descriptive Statistics for Interactive Communication

VAR	N	Mean		SD	Variance	Skewness		Kurtosis	
	Statistic	Statistic	SE	Statistic	Statistic	Statistic	SE	Statistic	SE
ICOM1	397	3.65	0.046	0.914	0.835	-0.781	0.122	0.684	0.244
ICOM2	397	3.78	0.049	0.968	0.938	-0.594	0.122	-0.072	0.244
ICOM3	397	3.88	0.046	0.916	0.839	-1.027	0.122	1.402	0.244

Table 5.9 presents descriptive statistics for interactive communication. Mean scores indicate positive perceptions of the participants regarding the perceived interactive communication of AI assistants. Low variance suggests homogeneity. Skewness (-0.781 to -1.027) and Kurtosis (<3) show non-normal distributions.

Table 5.10. Descriptive Statistics for Personalisation

VAR	N	Mean		SD	Variance	Skewness		Kurtosis	
	Statistic	Statistic	SE	Statistic	Statistic	Statistic	SE	Statistic	SE
PERS1	397	3.66	0.046	0.915	0.837	-0.621	0.122	0.324	0.244
PERS2	397	3.61	0.055	1.097	1.204	-0.569	0.122	-0.444	0.244
PERS3	397	3.77	0.045	0.895	0.801	-0.818	0.122	1.024	0.244
PERS4	397	3.91	0.042	0.836	0.700	-0.592	0.122	0.334	0.244

The mean scores of personalisation variables are positive (3.61 to 3.91), as shown in Table 5.10. Low variance indicates homogeneity. Skewness (-0.621 to -0.818) and Kurtosis (<1.204) suggest non-normal distributions of this factor.

Table 5.11. Descriptive Statistics for Attitude

VAR	N	Mean		SD	Variance	Skewness		Kurtosis	
	Statistic	Statistic	SE	Statistic	Statistic	Statistic	SE	Statistic	SE
AT1	397	3.84	0.043	0.860	0.740	-0.813	0.122	1.122	0.244
AT2	397	3.84	0.050	0.999	0.997	-0.778	0.122	0.212	0.244
AT3	397	3.87	0.048	0.953	0.908	-1.118	0.122	1.438	0.244

Upon observing the perceived attitude construct, which comprises three questions, it's evident that the mean values are positive (ranging from 3.84 to 3.87). This indicates that, on average, participants agree with the statements. Low variance suggests homogeneity. Skewness (-0.778 to -1.118) and Kurtosis (<0.997) indicate non-normal distributions.

Table 5.12. Descriptive Statistics for Usage Intentions

VAR	N	Mean	SD	Variance	Skewness	Kurtosis

	Statistic	Statistic	SE	Statistic	Statistic	Statistic	SE	Statistic	SE
UI1	397	3.79	0.043	0.852	0.726	-0.717	0.122	0.760	0.244
UI2	397	3.88	0.049	0.980	0.960	-0.727	0.122	-0.002	0.244
UI3	397	3.83	0.051	1.011	1.023	-0.943	0.122	0.705	0.244

The construct of usage intention comprises three questions. As shown in Table 5.12, presenting the descriptive statistics for each question, it is noticeable that the mean values for each item range from 3.79 to 3.88. This suggests that, on average, participants exhibit a willingness to use AI assistants and recommend them to others. Skewness (-0.717 to -0.943) and Kurtosis (<1.023) show non-normal distributions.

5.2.3 Assessment of Normality

The normality test is essential to the overall analysis of study data (Poncet et al., 2016). The two critical factors of normality are skewness and kurtosis (Cain et al., 2017). The skewness is a symmetry measurement; kurtosis signifies the peakiness of the data spread (Cain et al., 2017). The acceptable kurtosis and skewness values for average data spread between -2.00 and +2.00 (Bono, 2019). Therefore, if the kurtosis is less than 3, the dataset has lighter tails than a normal distribution (less in the tails), and if the skewness is less than -1 or greater than 1, the distribution is highly skewed (Field 2013). Therefore, as represented in Tables 5.7 to 5.12, the collected data for all variables are not normally distributed, based on the skewness and kurtosis values of this research that do not fall within the recommended range. Generally, when the sample size is more than 100, the Kolmogorov-Smirnov method is used for the normality test (Yazici & Yolacan, 2007). If the significance value (sig) is more significant than 0.05, then the data is stated to be normally distributed (Sormin et al., 2019). Tables 5.13 to 5.18 present the test of Kolmogorov-Smirnov for each construct. The departure of collected data from normality has several implications for the analysis and interpretation of results. Non-normal data can affect the validity of parametric statistical tests such as t-tests or ANOVA, which assume normality in the data distribution (Hau & Marsh, 2004). Using these tests on non-normal data can lead to inaccurate p-values and potentially incorrect conclusions about the significance of relationships or differences between variables. Therefore, it is essential to use appropriate statistical methods that do not rely on normality assumptions, such as non-parametric tests like bootstrapping techniques. These methods can provide more reliable results and accurate representation of the data's characteristics that are not biased by the non-normal distribution of the data.

Table 5.13. One-Sample Kolmogorov-Smirnov Test for PU

		PU1	PU2	PU3
N		397	397	397
Normal Parameters[a,b]	Mean	3.93	3.96	3.90
	Std. Deviation	0.806	0.924	0.960
Most Extreme Differences	Absolute	0.314	0.251	0.296
	Positive	0.252	0.172	0.200
	Negative	-0.314	-0.251	-0.296
Test Statistic		0.314	0.251	0.296
Asymp. Sig. (2-tailed)[c]		0.000	0.000	0.000

For this study, the data contains 397 samples; therefore, the Kolmogorov-Smirnov method was conducted to test for normality, as demonstrated in Tables 5.13 to 5.18. The significance values in all tables are less than 0.05 (alpha value) for all variables of this study. Thus, the collected data of this study are not normally distributed.

Table 5.14. One-Sample Kolmogorov-Smirnov Test for PE

		PE1	PE2	PE3
N		397	397	397
Normal Parameters[a,b]	Mean	4.03	4.07	4.01
	Std. Deviation	0.781	0.917	0.873
Most Extreme Differences	Absolute	0.293	0.251	0.306
	Positive	0.251	0.162	0.225
	Negative	-0.293	-0.251	-0.306
Test Statistic		0.293	0.251	0.306
Asymp. Sig. (2-tailed)[c]		0.000	0.000	0.000

Table 5.15. One-Sample Kolmogorov-Smirnov Test for ICOM

		ICOM1	ICOM2	ICOM3
N		397	397	397
Normal Parameters[a,b]	Mean	3.65	3.78	3.88
	Std. Deviation	0.914	0.968	0.916
Most Extreme Differences	Absolute	0.293	0.248	0.298
	Positive	0.211	0.167	0.213
	Negative	-0.293	-0.248	-0.298
Test Statistic		0.293	0.248	0.298
Asymp. Sig. (2-tailed)[c]		0.000	0.000	0.000

Table 5.16. One-Sample Kolmogorov-Smirnov Test for PERS

		PERS1	PERS2	PERS3	PERS4
N		397	397	397	397
Normal Parameters[a,b]	Mean	3.66	3.61	3.77	3.91
	Std. Deviation	0.915	1.097	0.895	0.836
Most Extreme Differences	Absolute	0.273	0.254	0.283	0.269
	Positive	0.198	0.143	0.213	0.215
	Negative	-0.273	-0.254	-0.283	-0.269
Test Statistic		0.273	0.254	0.283	0.269
Asymp. Sig. (2-tailed)[c]		0.000	0.000	0.000	0.000

Table 5.17. One-Sample Kolmogorov-Smirnov Test for AT

		AT1	AT2	AT3
N		397	397	397
Normal Parameters[a,b]	Mean	3.84	3.84	3.87
	Std. Deviation	0.860	0.999	0.953
Most Extreme Differences	Absolute	0.289	0.261	0.308
	Positive	0.223	0.162	0.208
	Negative	-0.289	-0.261	-0.308
Test Statistic		0.289	0.261	0.308
Asymp. Sig. (2-tailed)[c]		0.000	0.000	0.000

Table 5.18. One-Sample Kolmogorov-Smirnov Test for UI

		UI1	UI2	UI3
N		397	397	397
Normal Parameters[a,b]	Mean	3.79	3.88	3.83
	Std. Deviation	0.852	0.980	1.011
Most Extreme Differences	Absolute	0.295	0.259	0.276
	Positive	0.224	0.161	0.173
	Negative	-0.295	-0.259	-0.276

Test Statistic	0.295	0.259	0.276
Asymp. Sig. (2-tailed)[c]	0.000	0.000	0.000

5.3 Research Model Assessment

The proposed model assessments of a measurement model for the validity and reliability of latent constructs and a structural model for addressing the hypotheses and answering the research questions were assessed, as discussed in Chapter 4. This section discusses the results of the research model assessment via applying the partial least squares structural equation modelling (PLS-SEM) method. PLS-SEM is a multivariate technique that allows unobserved testing constructs, measurement, functional, predictive, and hypotheses of various indicators while considering measurement errors when statistically examining data (Hair et al., 2017).

The PLS-SEM method has the critical purpose of estimating, identifying, and evaluating the linear relationships between observed and unobserved constructs (Hair et al., 2017). Kock (2016) estimated path coefficients for hypothesis testing via the PLS-SEM method. The structural equation modelling method has two main parts: measurement and structural model assessment, as shown in Figure 5.4. The measurement model represents the relationships between the variables and the constructs. Therefore, the measurement model can determine if the constructs are accurately measured. However, the structural model represents the relationship between the factors only. Therefore, the structural model tests the hypothesised relationships (Kock, 2016). The structural equation modelling method is popular in marketing and social science studies as it is suitable for nonnormal data and supports small and large sample sizes (Hair et al., 2019). The results of the research's measurement and structural models are presented in the following sections.

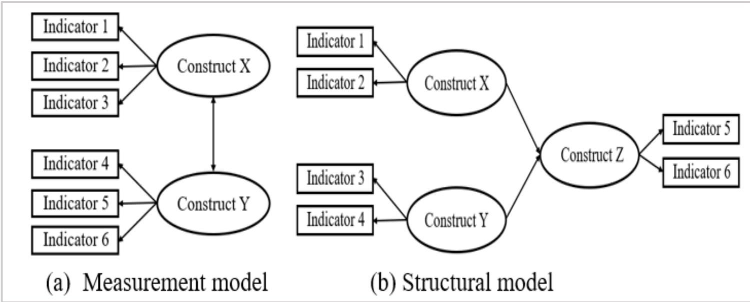

Figure 5.4. Two Main SEM Components

5.3.1 Measurement Model Assessment

The assessment of the validity and reliability of latent constructs involved the measurement scale. The quality of this scale is crucial for establishing the credibility and accuracy of research findings (Heale & Twycross, 2015). Consequently, scale quality is commonly determined through concepts of reliability and validity (Heale & Twycross, 2015). Therefore, Cronbach's alpha was used to test scale reliability, while convergent validity was measured via composite reliability, assessing the correlation of items within the construct. Additionally, discriminant validity was evaluated by measuring the average variance extracted and examining the correlation of items with those of other constructs. These measures collectively contribute to ensuring the robustness and accuracy of the research outcomes.

5.3.1.1 Internal Consistency and Scale Reliability

Table 5.19 provides the calculated scale reliability for all latent constructs employed in the current study. This verification process ensures the validity of the indicators within the research model through an assessment of internal consistency. Internal consistency, as defined by Tang et al. (2014), reflects the extent to which survey responses for all constructs remain uniform within a single measurement scale. The reliability of this measurement scale was evaluated using Cronbach's alpha, a measure of the estimated correlation among a set of indicators or items, as outlined by Bland and Altman (1997). Taber (2018) suggests that Cronbach's alpha values within the range of 0.60 to 0.70 are deemed acceptable, a viewpoint supported by Kline

(2015) who considers a Cronbach's alpha exceeding 0.60 as satisfactory. Construct reliability and validity results are detailed in Table 5.19.

Table 5.19. Measurement model- Construct Reliability and Validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE	Result
AT	0.763	0.764	0.864	0.679	Acceptable
ICOM	0.721	0.727	0.842	0.641	Acceptable
PE	0.742	0.744	0.853	0.660	Acceptable
PERS	0.669	0.680	0.798	0.498	Acceptable
PU	0.766	0.766	0.865	0.681	Acceptable
UI	0.794	0.796	0.879	0.708	Acceptable

The satisfactory reliability suggests the presence of internal consistency among the research constructs. The reliability at the construct level was examined, as shown in Table 5.19, which presents Cronbach's alpha values for all constructs. The reliability coefficients (Cronbach's alpha values) and the internal consistency of all the constructs of this study exceed the 0.6 level, indicating sufficient construct reliability (Kline, 2015; Field, 2009).

5.3.1.2 Assessment of Scale Validity and Model Fit

Regarding validity, two validity scales are considered: convergent and discriminant validity. Average Variance Extracts (AVE) were utilised for convergent validity with a threshold value of 0.5 or greater. According to Fornell and Larcker (1981), if the AVE value is below 0.5 and the composite reliability exceeds 0.6, the construct's convergent validity is still acceptable. Table 5.19 illustrates that all constructs have AVE values very close to 0.5 or greater than 0.6, indicating their convergent validity (Hair et al., 2019; Zaiţ & Bertea, 2011). For discriminant validity, the Fornell-Larcker criterion and cross-loadings were employed. Table 5.20 presents the Fornell-Larcker criterion analysis. Additionally, Table 5.20 shows that all the bold diagonal values are more significant than the horizontal and vertical diagonal values, confirming discriminant validity. Furthermore, Table 5.21, displaying the discriminant validity cross-loading, demonstrates that all the self-loading values of the individual items are more significant than the cross-loading of other items, reinforcing the discriminant validity of all constructs (Fornell & Larcker, 1981).

Table 5.20. Fornell-Larcker Criterion Analysis

VAR	AT	ICOM	PE	PERS	PU	UI
AT	**0.824**					
ICOM	0.766	**0.800**				
PE	0.602	0.532	**0.812**			
PERS	0.751	0.785	0.593	**0.706**		
PU	0.643	0.541	0.766	0.586	**0.825**	
UI	0.802	0.759	0.502	0.710	0.533	**0.842**

Table 5.21. Discriminant validity - Cross-loading

VAR	AT	ICOM	PE	PERS	PU	UI
AT1	0.814	0.608	0.548	0.581	0.533	0.628
AT2	0.807	0.632	0.441	0.635	0.478	0.674
AT3	0.849	0.652	0.498	0.639	0.575	0.68
ICOM1	0.552	0.798	0.337	0.588	0.326	0.573
ICOM2	0.592	0.779	0.386	0.604	0.406	0.593
ICOM3	0.683	0.824	0.533	0.684	0.545	0.649
PE1	0.461	0.394	0.806	0.424	0.601	0.378
PE2	0.468	0.41	0.797	0.477	0.638	0.379
PE3	0.535	0.488	0.834	0.539	0.626	0.463
PERS1	0.401	0.568	0.275	0.648	0.253	0.446
PERS2	0.492	0.582	0.226	0.689	0.28	0.518
PERS3	0.635	0.573	0.529	0.773	0.531	0.561
PERS4	0.553	0.515	0.58	0.707	0.529	0.473
PU2	0.529	0.467	0.641	0.502	0.797	0.453
PU3	0.561	0.484	0.614	0.522	0.849	0.47
UI1	0.712	0.635	0.456	0.604	0.461	0.849
UI2	0.653	0.636	0.414	0.618	0.453	0.831
UI3	0.658	0.645	0.394	0.572	0.432	0.845
PU1	0.501	0.388	0.64	0.427	0.829	0.396

In the examination of data from a composite model for a reflective measurement model, Henseler et al. (2016) emphasised the necessity of impartiality in the application of structural equation modeling techniques. The assessment of model fit indices was employed to gauge the fidelity of the measurement model in representing the data. Consistent with prior studies, this research computed the model fit indices, as suggested by Ramayah et al. (2017). Table 5.22 presents the outcomes of the model fit.

Table 5.22. Model Fit

	Saturated model	Estimated model
SRMR	0.091	0.1

d_ULS	1.574	1.916
d_G	0.567	0.6
Chi-square	1393.126	1413.067
NFI	0.675	0.67

For latent variables correlation, Table 5.23 displays each construct's value of one with its self-variables. The results indicated an acceptable level of the structural model fit, as shown in Table 5.22, signifying good factor loadings of all items into latent constructs and a well-fitted model. Furthermore, the correlation between variables is presented via the correlation plots, as shown in Figure 5.5.

Table 5.23. Latent Variables Correlation

	AT	ICOM	PE	PERS	PU	UI
AT	1	0.766	0.602	0.751	0.643	0.802
ICOM	0.766	1	0.532	0.785	0.541	0.759
PE	0.602	0.532	1	0.593	0.766	0.502
PERS	0.751	0.785	0.593	1	0.586	0.71
PU	0.643	0.541	0.766	0.586	1	0.533
UI	0.802	0.759	0.502	0.71	0.533	1

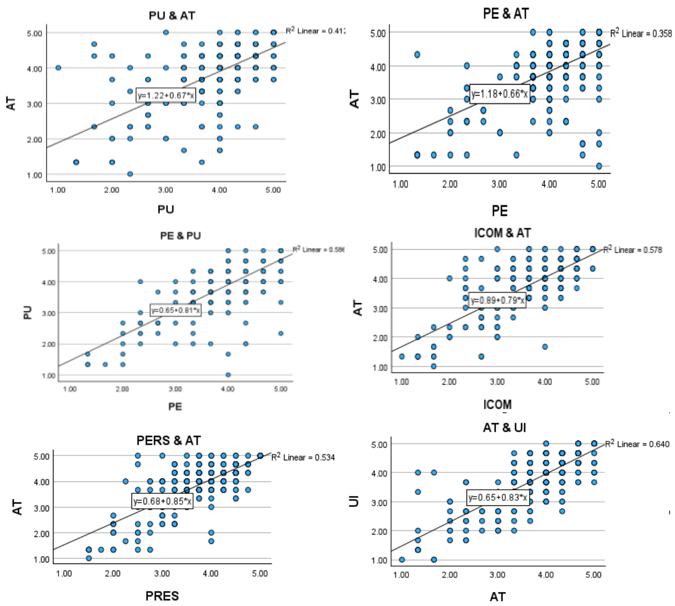

Figure 5.5. Scatter Plots for Relationship Paths

The above scatter plots, shown in Figure 5.5, visually represent the relationships between the variables. Each relationship path has a positive correlation, indicating that as one variable increases, the other also tends to increase. The r-square linear values, which are more than 0.3, indicate that the variation in the independent variable can explain the variation in the dependent variable. Therefore, the strong association between the variables reinforces the significance of the observed relationships in the study.

5.3.2 Structural Model Assessment

The structural model examines the predictions about the hypotheses and the subsequent determination of accepting or rejecting them based on the path coefficients. Figure 5.6 illustrates the conceptual framework, presenting all constructs and hypotheses. The SEM model was calculated to investigate the relationships between the constructs for users and non-users as the two separate datasets. The outcomes of the structural model assessment, including the values of the path coefficients, are presented in Figure 5.7. for users and Figure 5.8. for non-users. Additionally, Table 5.24 provides the calculations of the path coefficients in the research model, accompanied by their corresponding significance levels.

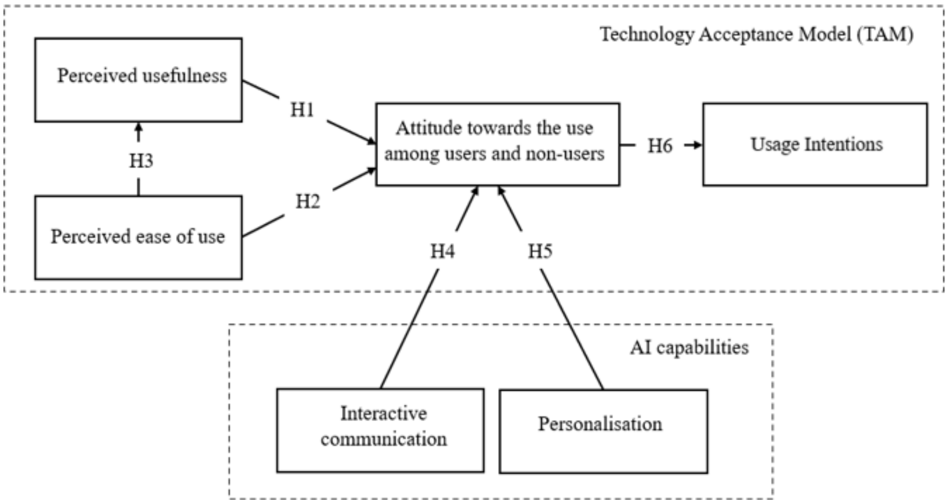

Figure 5.6. Research Conceptual Model

Table 5.24. Path Coefficients

PATH	β (NON USER)	β (USER)	Mean (NON USER)	Mean (USER)	STD (NON USER)	STD (USER)	t-value (NON USER)	t-value (USER)	*p*-value (NON USER)	*p*-value (USER)
AT -> UI	0.809	0.806	0.81	0.806	0.041	0.034	19.529	23.562	0	0

ICOM -> AT	0.396	0.266	0.396	0.266	0.069	0.073	5.698	3.645	0	0
PE -> AT	-0.119	0.283	-0.125	0.283	0.077	0.086	1.543	3.291	0.123	0.001
PE -> PU	0.56	0.791	0.579	0.791	0.107	0.038	5.219	20.692	0	0
PERS -> AT	0.239	0.266	0.249	0.262	0.081	0.061	2.954	4.395	0.003	0
PU -> AT	0.427	0.129	0.424	0.132	0.089	0.057	4.778	2.255	0	0.024

The results indicate from Table 5.24 that usefulness ($\beta = 0.427$, $p < 0.05$) for non-users and ($\beta = 0.129$, $p < 0.05$) for users influences the attitude towards using AI assistants for both non-users and users. The results mention that attitude positively influences (β =0.809, P < 0.05) for non-users and (β =0.806, P < 0.05) for users the behavioural intention of using AI assistants. Therefore, the end-user must have a positive attitude or perception towards AI assistants regarding their services to use this tool. Ease of use significantly influences users' attitude (β =0.283, P < 0.05). However, the results indicate that ease of use does not affect non-users' attitudes (β =-0.119, P = 0.123). Perceived ease of use positively impacts perceived usefulness for non-users (β =0.560, P < 0.05) and for users (β =0.791, P < 0.05).

Moreover, the results indicate that the AI assistant capability, which is interactive communication, positively affects the consumer attitude towards using AI assistants for both non-users ($\beta = 0.396$, $p < 0.05$) and users ($\beta = 0.266$, $p < 0.05$). The factor of personalisation significantly influences consumer attitude towards AI assistants for non-users ($\beta = 0.239$, $p < 0.05$) and for users ($\beta = 0.266$, $p < 0.05$). Therefore, H1, H3, H4, H5, and H6 are supported for users and non-users. H2 is just supported for users.

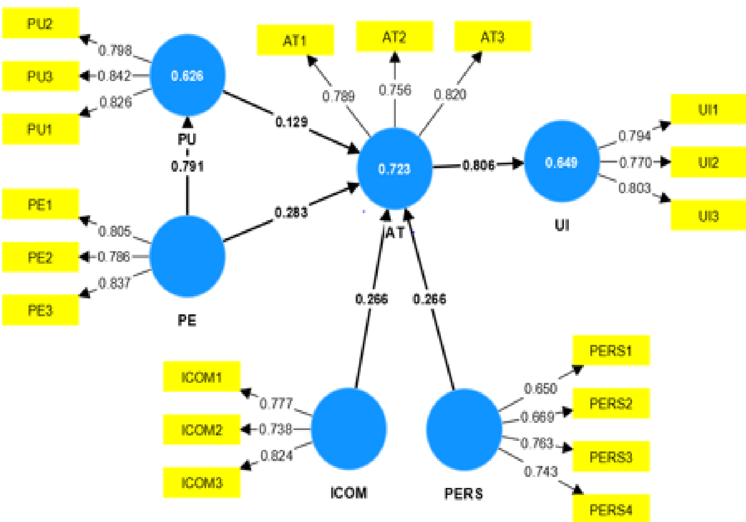

Figure 5.7. Tested Model for Users

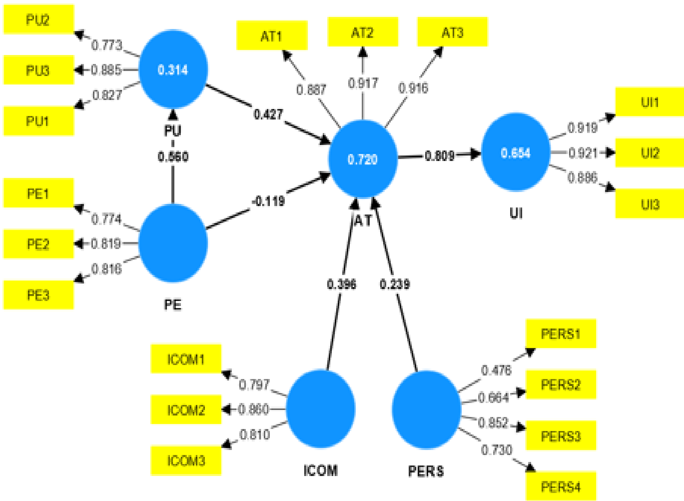

Figure 5.8. Tested Model for Non-Users

5.3.3 Multigroup Analysis

The multigroup analysis was conducted to test H7 and assess any differences between Western and Eastern cultures regarding the relationships among the primary factors influencing the intention to use AI assistants in e-commerce. Table 5.26 presents the results of the multigroup analysis, comparing path differences between the two groups. For all paths, the differences are less than 0.2, and p-values are greater than 0.5, indicating no statistical significance at the 0.05 level. Overall, the multigroup analysis suggests no significant differences in the relationships between constructs across the Western and Eastern groups, leading to the non-support of H7.

Table 5.25. Multigroup Analysis

PATH	Difference (Western - Eastern)	1-tailed (Western vs. Eastern) p-value	2-tailed (Western vs. Eastern) p-value
AT -> UI	-0.034	0.761	0.479
ICOM -> AT	-0.212	0.905	0.189
PE -> AT	-0.035	0.6	0.8
PE -> PU	-0.082	0.888	0.223
PERS -> AT	0.168	0.13	0.26
PU -> AT	0.146	0.142	0.283

The results indicate that the impact of usefulness and ease of use on attitudes toward using AI assistants is relatively equal in Western and Eastern cultures. Furthermore, the results show that the effect of AI capabilities on attitudes toward using AI assistants is also relatively equal in Western and Eastern cultures, and the impact of attitude on usage intention is likewise similar in both cultures. Therefore, there is a similarity between Western and Eastern cultures regarding their attitudes and adoption of AI assistants, which aligns with the concept of global consumer theory toward emerging technologies aiming to foster a sense of inclusion for global consumers and enhance various usages (Hernani-Merino et al., 2020).

5.4 Hypothesis Testing

As elaborated in the preceding sections, subsequent to evaluating the structural model, confirming its suitability, and examining the path coefficient, the subsequent sections delve into the path model concerning latent constructs. This is done to assess the hypotheses and their corresponding research questions in the present study. The results of hypothesis testing are presented in Table 5.26. The main research question of this study is: What key factors influence individuals' usage intention of AI assistants in e-commerce among users and non-users? The following sections address the research question by exploring each sub-question and hypothesis. The first sub-question is: How does perceived usefulness affect the attitudes of users and non-users towards using AI assistants in e-commerce? The following hypothesis is explored in this question as follow:

H1. Perceived usefulness positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

Regarding hypothesis H1, the research models in Figure 5.7 and Figure 5.8 show that perceived usefulness directly affects attitudes towards using AI assistants. The results show that hypothesis H1 is accepted. The second sub-question, how does perceived ease of use affect the attitudes of users and non-users towards using AI assistants in e-commerce? The following hypothesis addresses this question as follow:

H2. Perceived ease of use positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

Figure 5.7 and Figure 5.8 show that the relationship between the factor of the perceived ease of use and attitude of using AI assistants is not significant for non-users but is significant for users with path coefficients of 0.283. Accordingly, H2 is accepted for users. The third sub-question, How does perceived ease of use affect the perceived usefulness of users and non-users of AI assistants in e-commerce? This question is addressed in the following hypothesis:

H3. Perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants.

Table 5.24 shows that the perceived ease of use positively affects perceived usefulness and the path significance for users and non-users. H3 is supported. The fourth sub-question: How does interactive communication affect the attitudes of users and non-users towards using AI assistants in e-commerce? The following hypothesis is explored in this question as follow:

H4. Interactive communication positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

Table 5.24 shows the path significance of 0.396 for non-users and 0.266 for users. Therefore, hypothesis H4 is accepted. The fifth sub-question: How does personalisation affect the attitudes of users and non-users towards using AI assistants in e-commerce? It is related to the following hypothesis.

attitudesH5. Personalisation positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

Table 5.24 shows that the effect of personalisation on attitudes towards using AI assistants is significant for non-users and users. Accordingly, H5 is accepted. The sixth sub-question: How does attitude affect the intentions of users and non-users towards using AI assistants in e-commerce? This question is addressed in the following hypothesis:

H6. The attitudes will positively influence the usage intentions of users and non-users toward using AI assistants in e-commerce.

The second research question of this study: Do significant differences exist in the relations among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultures? This question is addressed in the following hypothesis:

H7. The relationships among the primary factors influencing the intention to use AI assistants in e-commerce differ significantly between Western and Eastern cultures.

Based on the data from Table 5.24 and Table 5.25, H6 is supported, while H7 is not. The findings indicate no significant differences between the two consumer groups. Table 5.25 reveals comparable patterns in the usage of AI assistants among Western and Eastern consumers, supporting this conclusion. The results suggest that regional or cultural variations between Western and Eastern consumers have a minimal impact on factors influencing their intentions and behaviour towards AI assistants in e-commerce.

Table 5.26. Hypothesis Testing

Hypotheses	Results
H1. Perceived usefulness positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.	Supported
H2. Perceived ease of use positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.	Supported for users Not supported for non-users
H3. Perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants.	Supported
H4. Interactive communication positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.	Supported

H5. Personalisation positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.	Supported
H6. The attitudes will positively influence the usage intentions of users and non-users toward using AI assistants in e-commerce.	Supported
H7. The relationships among the primary factors influencing the intention to use AI assistants in e-commerce differ significantly between Western and Eastern cultures.	Not supported

5.5 Chapter Summary

This chapter describes quantitative data analysis, descriptive statistics, and evaluation of the research framework to answer research questions and test hypotheses. The analysis of respondents' profiles confirms the suitability of the study sample. Moreover, descriptive data analysis reveals comprehensive insights about the collected data, showing a left-skewed distribution without extreme outliers. The measurement scale assessment demonstrates high construct reliability based on Cronbach's alpha values for all constructs, while scale validity and model fit tests confirm the validity of the measurement scale. Convergent and discriminant validity are established for the measurement scale and structural model assessments, ensuring an acceptable level of model fit for all constructs in the study.

Subsequently, the outcomes of the structural model assessment for this study are presented. The later sections of this chapter display the path coefficients obtained via the partial least squares structural equation modelling (PLS-SEM) approach and multigroup analysis. The path coefficients test supports hypotheses H1, H3, H4, H5, and H6, but not H2 and H7. Additionally, path coefficients of indirect effects were examined to test the research model between predictors and outcome variables. To support the results of the quantitative method and provide more insights into the research question, machine learning and natural language processing techniques were employed. In the upcoming chapter, the analysis of data related to the machine learning component in this investigation will be addressed.

Chapter 6. Qualitative Analysis and Results

6.1 Introduction

This chapter delves into the machine learning approach adopted in this study. Phase B involves conducting an analysis of online reviews using machine learning techniques to achieve two primary objectives: 1) analyse consumer reviews related to the online shopping experience and enhance the AI assistant usage experience for e-commerce, and 2) provide supportive evidence for the research questions and gain deeper insights into consumer attitudes and experiences. This phase employs three critical techniques for collecting and analysing online reviews: natural language processing (NLP), topic modelling, and thematic analysis. The analysis focuses on the attributes of the pre-defined main factors of the research model resulting from Phase A (quantitative study) of this research. As a result, the machine learning analysis aims to corroborate the quantitative results from the survey outlined in the previous chapter.

This chapter analyses publicly available online reviews of e-commerce channels used by the Louis Vuitton (LV) fashion brand. The rationale behind selecting Louis Vuitton (LV) as a case study for this phase is twofold: 1) LV is a top luxury brand in the fashion industry, and its consumers have high expectations of the online experience, and 2) LV has started integrating AI assistants into their shopping applications in some geographical locations. The data was collected from three publicly available technology review platforms: Trustpilot, the Apple Store app, and the Google Play Store.

This chapter begins by describing the review collection's aim, followed by data pre-processing and analysis procedures. Then, the findings of the NLP analysis and the relevant statements conducted by the thematic analysis are interpreted. Therefore, the chapter is structured as follows. Section 6.1 provides the introduction. Section 6.2 represents an overview of the collected online reviews. Sub-section 6.2.1 presents the outcomes of the data pre-processing.

As the second step before conducting the NLP analysis, sub-section 6.2.2 provides the data annotation and vectorisation stages and their results. Section 6.3 discusses the outcomes of the NLP analysis. Sub-section 6.3.1 demonstrates the effects of the keyword extraction from the collected online reviews. After that, sub-section 6.3.2 presents the LDA model. Section 6.4 presents the thematic analysis and integrative interpretation of the findings. Finally, Section 6.5 summarises and concludes the chapter.

6.2 Description of Online Reviews

A Python program was developed for web scraping. The Python scraper was explicitly designed to gather online data and implemented using Jupyter Notebook, installed through Anaconda 3 on a Windows operating system. The programmed scraper extracted online reviews and successfully collected a total of 997 reviews. The data collection process occurred in March 2022. These reviews were then compiled and organised in an Excel spreadsheet for further analysis and processing. The collected data primarily consisted of text and included four main categories: date, rank, review, and descriptions.

6.2.1 Data Pre-processing of Online Reviews

The data pre-processing involves specific steps to clean and prepare the collected reviews for the next stage: data analysis and interpretation. The first task of data pre-processing was data normalisation, which included converting all the collected reviews to standard text style. Therefore, all the text of the collected reviews was converted to lowercase, as shown in Table 6.1, which presents the results of the normalisation step. The second step of the data pre-processing stage is removing emoticons, punctuation marks, and digits. Moreover, the pre-processing data stage included a step of cleaning the collected text from multi-spaces and non-English languages. Remove stop words and spaces methods were conducted as the final data pre-processing step. Table 6.1 presents an example of the results of collected reviews after all phases of the data pre-processing stage. The following section discusses the consequences of data annotation and vectorisation methods.

Table 6.1. Data Pre-processing

No	Rank	Collected Review
0	2	anything to slow very load
1	5	It's everything, love it. This to about easy.
2	5	super
4	5	coolness
5	5	the easy navigation to
6	1	the new log is no longer on, but fine update.
7	1	able the login though logged off, it logs to now.
8	1	unable install to
9	5	awesome
10	5	they best have
11	1	the sure same login allows reason use some.
12	5	inexpensive people recommend for poor stuff.
13	1	design these do not old clothes diamond like som.
14	5	tech use to easily very high
16	5	fabulous always go to for your my sporting

6.2.2 Data Annotation and Vectorisation

After the data pre-processing and cleaning stage, data annotation was applied for the polarity mapping of each row in all collected reviews. Table 6.2 presents an example of the results of data annotating the collected reviews. The collected data was then converted into two sets bas ed on the rating given to each review, categorising them as either positive or negative sentime nt polarity. The vectorisation function was implemented to perform array operations on the co llected reviews. The total number of positive reviews is 423, and the number of negative revi ews is 523, as shown in Figure 6.1.

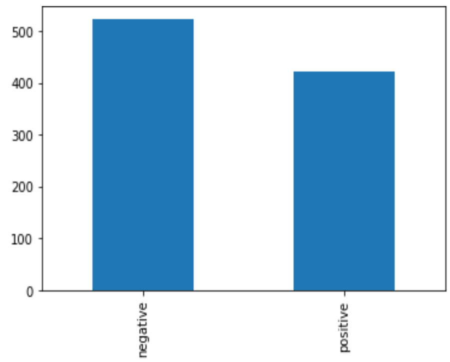

Figure 6.1. Positive and Negative Reviews

Table 6.2. Data Annotation and Vectorization

No	Rank	Collected Review	Polarity
0	2	anything to slow very load	negative
1	5	It is everything loves it this too about easy.	positive
2	5	super	positive
4	5	coolness	positive
5	5	the easy navigation to	positive
6	1	the new log is no longer on, but OK update.	negative
7	1	able the login though logged off, it logs to now.	negative
8	1	unable install to	negative
9	5	awesome	positive
10	5	they best have	positive
11	1	the same sure login allows reason use some t.	negative
12	5	inexpensive people recommend for poor stuff.	positive
13	1	design these do not old clothes diamond like som.	negative
14	5	tech use to easily very high	positive
16	5	fabulous always go to for your my sporting	positive
17	5	best clothes	positive
18	5	perfect	positive
19	5	pretty	positive
20	5	this to want to try it	positive

6.3 Natural Language Processing Analysis

This section presents the results of the natural language processing (NLP) analysis method applied to the collected online reviews. Researchers commonly use the NLP technique to comprehend natural language texts' structure, meaning, and sentiments, such as articles, tweets, and reviews (Grover et al., 2019). Through the NLP analysis, valuable insights were extracted regarding customers' attitudes, opinions, and experiences. Moreover, various linguistic aspects, including sentiment polarity, key phrases, and topics discussed in the reviews, were examined, enabling a comprehensive understanding of the overall sentiment distribution among the collected reviews and identifying specific aspects supporting the previous study's outcomes.

6.3.1 Keywords Extraction

The NLP analysis method involves a crucial step known as keyword extraction, which aims to identify the most important words or phrases in the given dataset. One widely used technique for this purpose is Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF is a statistical measure that evaluates the importance of a word to a document in a collection of documents. By assigning a weight to each word based on its frequency and the number of documents it appears in, TF-IDF can determine the significance of each word in the dataset. The higher the TF-IDF score, the more important the word is in the document.

The TF-IDF approach identifies the most critical comments in the dataset by considering the word's frequency and rarity across the entire dataset. Therefore, the TF-IDF method was applied for keyword extraction, effectively identifying essential words in the collected online reviews. As shown in Figure 6.1, this method reveals frequently used keywords in both positive and negative reviews, providing valuable insights into customer sentiments and experiences.

Figure 6.2. Frequently Used Keywords in Positive and Negative Reviews

The positive online reviews contain extracted keywords such as "great," "best," "love," "awesome," "fantastic," and "amazing," signifying the reasons for their positive classification. Conversely, the negative reviews include words such as "poor," "worst," and "never," which occurred frequently, indicating their negative sentiment. After the initial keyword extraction, the subsequent analysis focused on identifying the top 25 most frequently occurring three-word phrases in both positive and negative reviews, as presented in Table 6.3.

Table 6.3. The Top 25 of Three-Word Phrase Extraction

Three-word combination of positive reviews	TF-IDF	Three-word combination of negative reviews	TF-IDF
love louis vuitton	0.883673	stop killing animals	3.357308
great app beautiful	0.767295	killing animals products	3.218491
really love louis	0.547412	products fur fashion	2.910197
louis vuitton app	0.529536	animals products fur	2.910197
super easy use	0.519365	fur fashion furfree	2.778979
amazing customer service	0.516139	vuitton stop killing	2.498058
fantastic customer service	0.510883	louis vuitton stop	2.498058
really louis app	0.505753	dear louis vuitton	2.311668
love lv fashion	0.498725	poor customer service	2.038813
great company quality	0.477539	worst customer service	1.707281
easy navigate app	0.476897	lv customer service	1.268781
love really expensive	0.476216	horrible customer service	0.947408
love every day	0.475776	awful customer service	0.935765
love easy clean	0.475443	will never order	0.866403
pleased product service	0.470301	terrible customer service	0.859143
received package lv	0.466086	anything louis vuitton	0.829997
beautiful stuff world	0.464709	disappointed customer service	0.821797
app rich people	0.464504	shocking lv customer	0.767653
love quality aesthetics	0.464142	customer service ups	0.767653
cooooooooolest app world	0.452346	will never buy	0.736076
love fashion thats	0.451784	buy anything louis	0.716149
application fastgood service	0.448646	never order online	0.708992
want try products	0.448584	cant buy anything	0.691411
blame ups lv	0.447481	ordered wallet online	0.671768
useful awesome loving	0.446474	ridiculous customer service	0.593248

Among the identified phrases, "super-easy use," "easy navigate the app," and "useful awesome loving" were indicative of positive reviews. On the other hand, terms like "poor customer service," "horrible customer service," and "never order online" were prevalent in negative reviews, clearly expressing customers' dissatisfaction with the corresponding service. Overall, identifying frequently occurring three-word phrases in positive and negative reviews provides deeper insights into the expressed sentiments and specific experiences that led to these evaluations.

6.3.2 Topic Modelling

Various machine-learning techniques can be employed to analyse text datasets and extract valuable insights. One such technique is Latent Dirichlet Allocation (LDA) topic modelling, widely used in (NLP) applications to identify hidden topics in a text corpus. In the current study context, the LDA topic modelling was utilised to analyse a dataset of online reviews and identify their most relevant topics. The identified cases provide a comprehensive understanding of the customers' preferences, expectations, and concerns, enabling businesses to improve their service and meet customer needs. Additionally, the LDA topic modelling analysis reveals the probability distribution of each topic in the positive and negative reviews. The LDA model was then applied separately to each group to identify the main themes in the online reviews. The

LDA model analysis identified twenty topics within the reviews. Each topic includes a set of ten words, specifically for positive and negative online reviews. These identified topics provide valuable insights into the prevalent themes and concepts within the collected reviews, shedding light on the aspects that customers frequently emphasise.

6.4. Thematic Analysis and Integrative Findings

Thematic analysis is a method used to identify patterns in qualitative data, such as customer reviews. In the current study, thematic analysis was utilised to analyse the themes and topics expressed in customer reviews about their online shopping experience. The objective was to identify improvement areas based on the analysis's findings. Table 6.4 presents the thematic analysis, revealing themes and topics in both positive and negative application reviews. By examining these themes, developers could gain insights into the areas where customers were satisfied or dissatisfied, using this information to enhance the AI assistants for online shopping.

Table 6.4. Thematic Analysis

Predefined theme	Feature	Example of review
Usefulness	➢ Images/View ➢ Fast response ➢ Search/Find ➢ Category/Navigate ➢ Updated information	• "Love the App & Very Helpful and Informative. Thank You Guys so Much." • "Especially during the pandemic, this app has been so much help. It is so nicely built and has exactly what I am looking for, every time." • "Useless and too confusing. I downloaded the app to get the holiday stickers and still could not get them."
Ease of use	➢ Find/search feature ➢ Easy to navigate ➢ Easy to shop ➢ Accessibility ➢ Hard/inconvenience	• "Fast and super easy to use loved it." • "This is a great job super easy to find what I'm looking for when shopping." • "Out of sudden all prices display in SGD and cannot change currency, very inconvenience."
Personalisation	➢ Individual needs ➢ More products ➢ Software compatibility	• "It has all the stuff I needed it has luggage to bumbags to watches this the best app for online shopping for Louis Vuitton I highly recommend this app." • "Needs more bags to buy." • "Need to compatibility for Samsung tab s6."
Communication	➢ Classy and pleasant conversation	• "I've had very good experiences. Classy, pleasant conversation, efficient and helpful. Minus one star only for delayed notification." • "I have been using a customer support chat for ordering some items and received impeccable service. The items were actually marked as out-of-stock on their website and the customer support assistant was able to locate them for me."

Additional findings
➢ Payment Accessibility ➢ Save time & Notification ➢ Wish list • "This app won't allow me to create an account in short, it's not working. what a waste of time." • "When I try to check out with PayPal it tells me access denied" • "Minus one star only for delayed notification about the date of delivery in one instance." • "Can't save items to wish list. The existing wish list can't be synced either.

The thematic analysis findings were utilised to explore all the primary constructs resulting from the survey analysis. The results indicate that usefulness, ease of use, personalisation, and interactive communication positively influence consumer attitudes. These findings align with the evidence from the thematic analysis, providing complementary insights. Furthermore, the thematic analysis offered additional insights, enriching the interpretation of the quantitative results. For instance, some customers expressed concerns about the security and privacy of their personal information when using the application, highlighting potential areas for improvement. Developers could use this feedback to enhance AI assistants' security and privacy features and protect customers' data. Table 6.5 presents the integrated analysis interpretation of the mixed method.

Table 6.5. Integration Analysis

Dimensions	Quantitative Results	Qualitative Results (in all dimensions captured in predefined themes)	Nature of Integration /Complementary
Usefulness	Consumers who perceive AI assistants as more useful tend to have more favourable attitudes towards using them in e-commerce applications.	Consumers appreciate the helpful images, updated information, and fast responses to a conversation provided during their online shopping experience.	The integration of the quantitative and qualitative findings suggests a complementary. The quantitative data indicates that perceived usefulness positively impacts attitudes, while the qualitative data reinforces this finding by highlighting the specific aspects of helpfulness aspects based on consumers' experience.
Ease of use	Consumers who perceive AI assistants as easy to use tend to have positive attitudes towards using them.	Online shoppers value product searching, visual displaying, recommendation, navigation, accessibility, and interactions during online shopping.	The quantitative data showed that the factor of ease of use is a positive effector towards the consumers' attitudes, and qualitative data supports this finding by emphasising the key elements of ease of use based on consumers' experience.
Personalisation	If AI assistants can offer personalised experiences for consumers, their attitude towards AI assistant use is likely to be significantly more positive.	Consumers express satisfaction with personalised products and suggestions based on their needs.	The quantitative data showed that personalisation positively affects the consumers' attitudes. In contrast, qualitative data supports this finding by highlighting how consumers value receiving services or products customised to their specific needs.
Communication	AI assistants' interactive communication capability significantly impacts consumers' attitudes towards AI assistant use.	Consumers appreciate the experience of classy, pleasant, and efficient communication during online conversations.	The quantitative data showed that interactive communication significantly influences consumers' attitudes, and qualitative data supports this finding by identifying how the style of conversations leads to customers' satisfaction.

The reviews highlighted several key themes related to customer service, app functionality, user-friendliness, personalisation, product quality, and interactive communication and delivery.

Positive reviews praised helpful and responsive customer service representatives, easy-to-use app functionality, user-friendliness, and high product quality. In contrast, negative reviews criticised slow response times, unhelpful customer service, bugs, crashes, glitches in the app, difficult navigation, poor product quality, and slow and unreliable delivery. These insights provide valuable feedback for developers to improve AI assistants' quality, stability, user experience, product offerings, and delivery services to effectively meet customer needs and preferences.

Table 6.5 presents the integration analysis of quantitative and qualitative results for different dimensions of AI assistant usage. The findings show that perceived usefulness positively impacts consumers' attitudes, with qualitative data emphasising helpful images, updated information, and fast responses during online shopping. Similarly, ease of use positively affects attitudes, with qualitative data highlighting key elements such as product searching, visual displaying, and interactions. Personalisation also influences attitudes positively, with consumers valuing customised products and suggestions. Interactive communication significantly impacts attitudes, as consumers appreciate pleasant and efficient conversations. Integrating quantitative and qualitative findings indicates a complementary relationship, strengthening the overall understanding of consumers' attitudes towards AI assistant use in e-commerce applications.

6.5 Chapter Summary

This chapter presents a comprehensive analysis of customer reviews from fashion e-commerce platforms using natural language processing. It involves extracting keywords to identify frequently occurring words in positive and negative reviews. Additionally, the study identifies the most frequently occurring three-word phrases in both positive and negative reviews. Furthermore, applying LDA topic modelling and thematic analysis provides deeper insights into specific customer experiences, enhancing the interpretation of quantitative results.

Chapter 7. Discussion, Implications and Conclusion

This chapter presents discussions of the findings and recommendations of the study. Section 7.1 revises the research aim, objectives, questions, and hypotheses. Section 7.2 discusses the analysis of the study's findings, and Section 7.3 provides the critical contributions of the theoretical and practical implications of the study. Finally, Section 7.4 identifies the study's limitations and provides recommendations for future research.

7.1 Research Aim and Questions

As AI continues to transform the online shopping landscape, understanding what drives individuals' decisions to engage with AI assistants is crucial for businesses and customer satisfaction. Recently, AI-powered assistants have gained popularity in e-commerce, offering personalised and efficient customer experiences. However, despite their growing prominence, there are limited studies on AI assistant adoption in e-commerce and a lack of empirical research focusing on both users and non-users as potential users of AI assistants. Previous studies have also provided contradictory evidence regarding some factors influencing the intention to use AI assistants, considering a specific cultural context. With these considerations, the primary objective of this study was to explore the fundamental factors influencing individuals' attitudes and usage intentions toward AI assistants in e-commerce, encompassing both users and non-users. Additionally, this study aimed to recognise cultural differences to provide valuable insights into diverse consumer preferences. The following main research question with its sub-questions have guided the process:

Main Research Question: What factors influence individuals' intention to use AI assistants in e-commerce among users and non-users, and are there significant differences in these factors impact when comparing Western and Eastern cultures?

To address this question, a literature review on adopting AI assistants in e-commerce was conducted to explore recent studies on this topic. This review led to the development of the research model along with sub-questions. Figure 7.1 presents this study's research model and the total number of hypotheses.

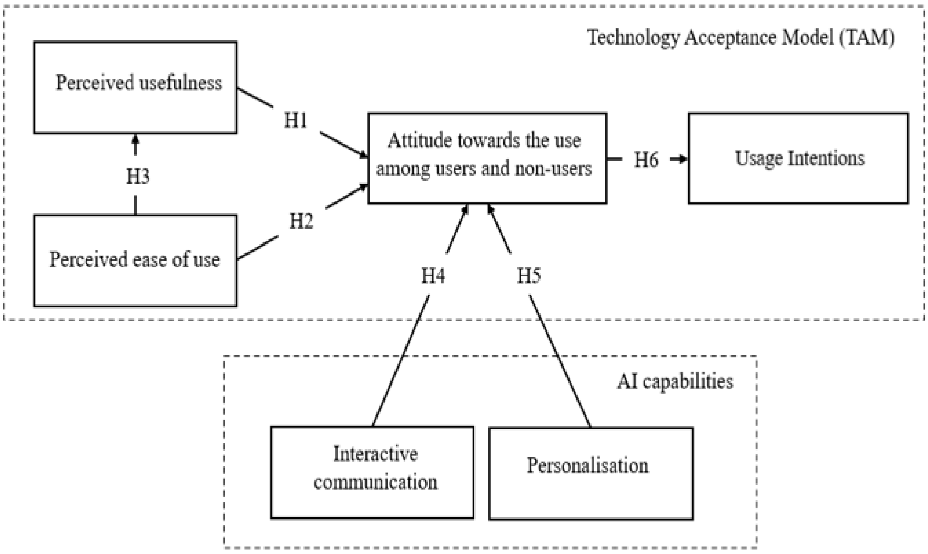

Figure 7.1. Research Structural Model

The sub-questions for the main research question, derived from the research model, were:

RQ1.1: How does perceived usefulness affect the attitudes of users and non-users towards using AI assistants in e-commerce?

RQ1.2: How does perceived ease of use affect the attitudes of users and non-users towards using AI assistants in e-commerce?

RQ1.3: How does perceived ease of use affect the perceived usefulness of users and non-users of AI assistants in e-commerce?

RQ1.4: How does interactive communication affect the attitudes of users and non-users towards using AI assistants in e-commerce?

RQ1.5: How does personalisation affect the attitudes of users and non-users towards using AI assistants in e-commerce?

RQ1.6: How does attitude affect the intentions of users and non-users towards using AI assistants in e-commerce?

RQ1.7: Do significant differences exist in the relations among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultures?

7.2 Findings

The present research findings were obtained from a mixed-method approach using quantitative and qualitative studies. The total number of collected data for both studies is 1,397. The discussion of the findings is presented in the following subsections, arranged around each hypothesis and its respective results. The linkage between the research sub-questions and the hypotheses is as follows:

RQ1.1: How does perceived usefulness affect the attitudes of users and non-users towards using AI assistants in e-commerce?

- **H1.** Perceived usefulness positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

RQ1.2: How does perceived ease of use affect the attitudes of users and non-users towards using AI assistants in e-commerce?

- **H2.** Perceived ease of use positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

RQ1.3: How does perceived ease of use affect the perceived usefulness of users and non-users of AI assistants in e-commerce?

- **H3.** Perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants.

RQ1.4: How does interactive communication affect the attitudes of users and non-users towards using AI assistants in e-commerce?

- **H4**. Interactive communication positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

RQ1.5: How does personalisation affect the attitudes of users and non-users towards using AI assistants in e-commerce?

- **H5.** Personalisation positively influences the attitudes of users and non-users towards using AI assistants in e-commerce.

RQ1.6: How does attitude affect the intentions of users and non-users towards using AI assistants in e-commerce?

- **H6**. The attitudes will positively influence the usage intentions of users and non-users toward using AI assistants in e-commerce.

RQ1.7: Do significant differences exist in the relations among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultures?

- **H7.** The relationships among the primary factors influencing the intention to use AI assistants in e-commerce differ significantly between Western and Eastern cultures.

7.2.1 Usefulness

The path "PU -> AT" exhibits differing coefficients between user groups (β=0.12), with a stronger impact on non-users (β=0.42), as reflected by the higher t-value for users (2.25) and non-users (4.77) and significant p-value (users=0.02 and non-users=0.00). Thus, the hypothesis that usefulness positively influences users and non-users towards using AI was supported. Meanwhile, the results of another investigation underscore the noteworthy effects of factors such as the perceived usefulness of a mobile app on users' intentions to utilise the mobile application and their overarching attitude towards it (Hasan et al., 2021). In addition, previous empirical research has established the impact of perceived usefulness on consumer attitudes, as exemplified by its influence on attitudes towards the adoption of social media (Alduaij, 2019). Furthermore, another study's outcomes affirm each hypothesised relationship's favourable and statistically significant results. In contrast, the variable of perceived usefulness stands out as a particularly robust predictor, exerting a significant influence on individuals' overall experiential outcomes when using chatbots (Lubbe & Ngoma, 2021). Meanwhile, a mediating role played by the perceived usefulness of AI was also highlighted, indicating that functional AI, as opposed to socially oriented AI, engenders a heightened sense of perceived usefulness. This, in turn, cultivates more favourable attitudes towards AI and a heightened perception of AI's realism. These outcomes collectively hold significant ramifications for human-AI communication and human-machine interaction research, accentuating the importance of understanding the differential impacts of AI types on users' perceptions and attitudes (Kim et al., 2021).

For users, the perception that AI offers tangible benefits, aids in tasks, or enhances their overall experiences leads to higher satisfaction, efficiency, and effectiveness in their interactions. Similarly, the perception that AI can be functional, relevant, and practical for non-users encourages a more favourable disposition towards AI adoption. By recognising AI's potential value and advantages, non-users are more likely to overcome hesitations from unfamiliarity or scepticism, thus fostering a more positive attitude towards AI. In both cases, the perceived usefulness of AI serves as a catalyst, prompting users and non-users alike to perceive AI as a valuable tool that augments capabilities and contributes positively to their experiences, thereby fostering a receptive stance towards its adoption.

Zarouali et al. (2018) description of perceived usefulness shows that it is inherently linked to ease of use. In this context, the perceived usefulness alludes to the perceptions consumers have concerned productivity or task performance when using AI assistants in e-commerce. Premised on the TAM model, the perceptions concerning ease of use tend to vary among people (Lee & Lin, 2023; Shin, 2010). Cultural factors can be a significant influence on such perceptions. This is aligned with the conceptualisations emerging from SET and the Theory of Reasoned Action that social interactions, subjective norms, and influences from the social environment influence customer satisfaction and attitudes when using AI assistants (Jiang et al., 2022; Roh et al., 2023). The findings in the current study align with the conceptual framework by demonstrating that positive attitudes emerging from the perceived usefulness increases the intentions to use AI assistants in e-commerce for customers from different cultural background. Therefore, assessing the perceived usefulness in the current study fosters an understanding of how the effectiveness of AI assistants in meeting customer needs and expectations transcends the cultural aspects. Also, the findings on the perceived usefulness are inherent in establishing the value customers ascribe to AI assistants during their shopping experience. Suggestively, positive attitudes associated with perceived usefulness imply that AI assistants are a valuable aspect of the shopping experience.

7.2.2 Ease of Use

The path "PE -> AT" displays differing coefficients between non-users and users, indicating a negative influence of Perceived ease of use on Attitude for non-users (β=-0.11) and a positive influence for users (β=0.28), with the latter exhibiting higher t-values (users=20.69 and non-users=5.21) and significant p-value for users=0.001 group while non-significant value for non-users=0.12. Thus, the hypothesis was that with the favourable disposition towards ease of use, users were positively impacted by the perceived level of simplicity in its operation, while non-users found it challenging. The possible explanation for this can be that the users respond positively when they perceive that interacting with the technology is straightforward and uncomplicated. This positive response arises from their familiarity and experience with the system, enabling them to navigate and utilise it confidently. On the other hand, non-users lacking prior exposure to the technology may find its operation more challenging due to their unfamiliarity. The unfamiliarity can lead to uncertainty and hesitancy in their interactions, thus impacting their perception of ease of use. Overall, users' positive experiences with the technology's simplicity contrast with non-users' challenges stemming from their lack of familiarity, underscoring the role of prior experience in shaping perceptions of ease of use.

These findings are consistent with similar studies that found a positive relationship between usefulness perception and attitude toward using AI (Hasan et al., 2021; Ashfaq et al., 2020; Zarouali et al., 2018). Similarly, another study investigated consumers' opinions and purchasing intentions toward AI technology (Yin & Qiu, 2021). The study included 313 respondents (61% female) between 18 and 65 from the top ten metropolitan regions in the US. According to the findings, perceived usefulness, simplicity of use, and performance risk all affected customers' attitudes toward AI—positive opinions about the technology involved buying intentions favourably (Liang et al., 2020). Furthermore, antecedent scholarly research has substantiated the impact of perceived usefulness on consumer dispositions, exemplified by its effect on attitudes towards the adoption of social media, as evidenced by Alduaij (2019). Furthermore, the outcomes of another study affirm the positive and statistically significant consequences of each hypothesised relationship. In contradistinction, perceived usefulness assumes paramount importance, emerging as the preeminent predictor exerting a substantial influence on individuals' comprehensive experiential outcomes in the context of chatbot utilisation, as elucidated in the investigation conducted by Lubbe and Ngoma (2021). Consumers' perceptions about the usefulness of AI platform usage significantly determine their attitude towards AI-based e-commerce platforms. However, regardless of apparent utility or simplicity of use, the requirement for human contact cannot be replaced by AI in particular cultural settings (Kelly et al., 2023). In addition, another study illuminates the significant role of ease of use in influencing consumers' disposition to trust and embrace AI technology within online retail operations (Nagy & Hadjú, 2021). By comprehending the determinants (ease of use) underlying customer utilisation and impediments, organisational leaders and developers can formulate and implement these pioneering technologies more effectively, augmenting the customer experience and elevating organisational performance (Jan et al., 2023). In contrast, empirical findings proposed that perceived ease of use does not maintain a statistically significant correlation with the dependent variable (Tan & Lim, 2023).

Tahar et al. (2020) described the perceived ease of use as how individuals subjectively assess learning and using a particular technology. Zarouali et al. (2018) link it to perceived usefulness as the practical and effortless capacity to enhance productivity or task performance when using AI shopping assistants. This relationship between perceived ease of use and usefulness is demonstrated in the conceptual framework as a combination of factors that influence the customers' attitudes. According to Teo et al. (2009), the TAM model demonstrates that positive beliefs can lead to increased intentions to adopt and continue using AI assistants because of the positive attitude users have towards the technology. The insights emerging from the findings align with the conceptual and TAM theoretical framework, considering that the beliefs and attitudes emerging among the consumers who engage with AI assistants shape their behavioural intentions. If an individual believes that the AI assistants are complex, there is limited intention implying that they have a negative attitude towards the technology. The findings on perceived ease of use help to differentiate how attitudes that emerge among users and non-users develop and how they differ based on experience in the use of AI assistants. Acikgoz and Vega (2022) note that the TAM model is appropriate in investigating novel technologies, which makes findings on the perceived ease of use in the context of users and non-users in a multicultural context significant in informing how perceived usefulness impacts adoption and intentions to continue using the AI assistants in e-commerce.

7.2.3 Ease of Use Positively Influences Usefulness

The ease of use to usefulness pathway displays differing coefficients of 0.56 for non-users and a notably higher 0.791 for users, both associated with highly significant t-values of 5.219 and 20.692, respectively. Thus, the hypothesis that perceived ease of use positively influences perceived usefulness among users and non-users of AI assistants was well supported by both groups. Hence, the positive influence of ease of use on perceived usefulness is rooted in the cognitive benefits of reduced complexity, increased user proficiency, heightened efficiency, and enhanced overall user experience. As users find the AI technology easy to navigate and integrate into their tasks, their perceptions of its usefulness are positively reinforced, fostering a more favourable disposition towards its utilisation.

Theoretically, a user's and nonuser's acceptance of a particular technology is influenced by two noteworthy variables: the perception of AI usefulness and ease of use, notwithstanding the assertion that the latter exerts a comparatively lesser impact, as Cha (2010) indicates. However, in both (Users and Non-users) cases, the positive relationship between perceived ease of use and usefulness can be attributed to the cognitive alignment between perceived ease of use and the perceived usefulness of AI assistance. An interface that is easy to navigate and understand aligns with mental models of the users and non-users, reducing perceived complexity and increasing the likelihood of successful task completion. This alignment bolsters the perception that the technology is effective and advantageous, consequently fostering positive attitudes and increasing AI assistants' perceived usefulness among users and non-users. Furthermore, similar results were observed in a study administered an online survey among a sample of 400 individuals who are residents of Jakarta and employ smartphone voice assistants. Employing SmartPLS to assess validity, reliability, and the study's hypotheses, the outcomes substantiate the validity of all six research hypotheses. The findings affirm the constructive effect of perceived ease of use on perceived usefulness, signifying a statistically significant association between the two constructs (Oktavia et al., 2023). Moreover, Noreen et al. (2023) demonstrated a noteworthy and affirmative correlation between the intention to embrace AI and critical factors encompassing perceived usefulness and ease of use of AI technology.

Zarouali et al. (2018) describe the perceived usefulness and ease of use as factors that determine the practical and effortless use of AI shopping assistants that lead to increased productivity or task performance. Based on the conceptual model adopted in the current study, the influence that perceived usefulness and ease of use have on customers is parallel and complementary. Therefore, the positive attitudes associated with the perceived usefulness are inherently linked to those of the perceived ease of use. These sentiments are aligned with the TAM model, which employs perceived usefulness and ease of use as the primary factors in the assessment of users' attitudes and intentions to use a particular technology (Davis, 1989). The impact of perceived ease of use on the perceived usefulness of AI assistants highlights the influence cognitive abilities have on the attitude and intentions to use the technology. The findings show that customers with adequate access to information and knowledge can effectively learn and use AI assistants. Developing relevant technological skills leads to positive perceptions concerning the ease of use, which subsequently creates a positive attitude and intention to continue using because individuals feel that the technology is useful. These findings show that users have experience and knowledge, which makes them more likely to develop a positive attitude and intention to use AI assistants compared to non-users. In this context, the findings are important in highlighting why the deployment of AI assistants should be coupled with adequate sharing of information that can enable all users to develop the relevant skills to realise the benefits associated with the technology in their shopping experience.

7.2.4 Interactive Communication

The "ICOM -> AT" path indicates positive coefficients for non-users (β=0.39) and users (β=0.26). However, the t-values are relatively higher for non-users (5.69) than users (3.64) with a significant p-value (0.00), implying a stronger effect of Interactive Communication on Attitude for non-users. The results indicate that interactive communication positively affects consumer attitudes towards AI assistants. Questions can arise about why interactive communication has a positive effect, and the possible explanation can be the engagement, personalisation, perceived responsiveness, and integration aspects of interactive AI interactions collectively foster favourable attitudes by resonating with innate human psychological inclinations and cognitive processes.

This study explicitly assessed interactive communication as a critical characteristic of AI assistants. This finding indicates that well-designed AI assistants' communication styles and customised features significantly influence consumers' attitudes towards AI-based platforms. The statistical analysis strongly supports a substantial relationship between AI assistant characteristics and consumers' attitudes, thus confirming Hypothesis 4. These findings emphasise the profound impact of well-designed conversational AI interfaces on consumers' attitudes towards AI platforms. They underscore the importance of delivering services that align with consumers' expectations, fostering positive attitudes and enhancing consumers' intention to utilise AI e-service platforms (Elsholz et al., 2019). While prior research in AI assistant design has raised concerns about the potential adverse effects of imbuing AI assistants with high levels of human likeness (Kim et al., 2021), scholarly discourse has consistently emphasised the importance of endowing AI assistants with specialised expertise, particularly within the domain of e-commerce (Liew et al., 2021). Consequently, drawing from established principles within marketing and communication literature, the strategic integration of interactive communication is advocated to showcase the adept proficiency of AI assistants within the context of e-commerce. Preceding empirical investigations have substantiated that interactive communication is a robust predictor of attitudes toward online communicators (Lee et al., 2015). Moreover, this study found that interactive communication is crucial for e-commerce applications. For example, a consumer mentioned that good experiences with customer service applications include classy, pleasant, and efficient conversation. These results are consistent with the literature (Ahmed et al., 2022; Svikhnushina et al., 2021; Yang et al., 2019; Cheng & Jin, 2019), which highlights that analysing consumer reviews is a significant way to improve the technology to meet consumers' needs and preferences. Interactive communication in e-commerce AI applications is crucial for creating engaging, personalised, and satisfying customer experiences. Facilitating effective information exchange, customisation, and support contributes to increased customer engagement, loyalty, and, ultimately, the success of e-commerce businesses. The strength of the result is not surprising since AI virtual assistants have a wide range of benefits to business firms and consumers. AI assistants enable online consumers to prompt any information related to products. Consumers were able to recognise the benefits of AI assistants, and this may explain why interactive communication is a significant determinant of attitude.

Interactive communication alludes to the AI shopping assistant's capacity to facilitate two-way communication for a personalised experience (Chung et al. 2020; Srinivasan et al. 2002). Effective interactive communication entails a bidirectional exchange of information in real-time (Abeele, 2007). According to Kim et al. (2023), AI assistance is more effective when they facilitate real-time communication with the users to ensure timely response and feedback that can accelerate meeting the customer needs and enhance their shopping experience. These insights are aligned with TAM and the conceptual framework because effective communication influences the attitudes and intentions to use AI assistants by enhancing the perceived usefulness (Ikumoro & Jawad, 2019). Furthermore, the perceived ease of use determines successful interactive communication between the customers and the AI assistant requires. Suggestively, individuals who find the system difficult to use are less likely to engage in interactive communication. Insights emerging from the influence interactive communication has on attitudes towards AI assistants facilitate an understanding of how people from different backgrounds relate to the anthropomorphic features of AI assistants. It also highlights how languages and other cultural aspects associated with interactive communication between companies and customers are integrated into the AI shopping assistant experience. Such considerations are critical in enhancing the quality of services offered by the AI assistant and taking a personalised approach to customer satisfaction (Choi et al., 2020; Dwivedi et al., 2022).

7.2.5 Personalisation

The "PERS -> AT" path indicates positive coefficients for non-users (β=0.23) and users (β=0.26). While the t-values are relatively lower for non-users (2.95) than users (4.39) with a significant p-value (Users=0.00 and non-users=0.003), implying a stronger effect of personalisation on Attitude for non-users. Thus, the findings suggest that personalisation in AI assistants favours consumers' disposition towards adopting AI assistants. Meanwhile, incorporating personalisation attributes into AI assistants cultivates a harmonious relationship between consumers and technology. Through tailored experiences, trust-building, enhanced efficiency, and alignment with prevailing cultural norms, personalisation emerges as a pivotal driver in fostering consumers' favourable disposition towards adopting AI assistants.

Contemporary advancements in electronic commerce AI platforms are distinctly centred on providing tailored configurational alternatives, aiming to cater to distinct individual preferences, as elucidated by Wu et al. (2020). For example, the luxury brand Gucci has implemented a chatbot mechanism, which serves as a conduit for dispensing bespoke promotional communications to targeted patrons who express a keen interest in personalised merchandise, as detailed in the study by Chung et al. (2020). Furthermore, the empirical exploration herein focuses on a specific demographic subset: female consumers engaged in fashion retail within the United Kingdom subjected to personalised promotional overtures. The outcomes emerging from this case study demarcate a pronounced inclination among these participants towards seeking economic concessions for items of interest, concomitant with an aspiration to elevate their in-store experiential encounters. However, it is discerned that these consumers exhibit a discernible aversion towards instances of disruptive interventions and generic promotional gestures. Concurrently, a conspicuous propensity towards exercising autonomous control surfaces alongside endeavours to regulate the disclosure of sensitive personal information and ameliorate the calibre of recommendations procured. Of noteworthy significance, comprehensive analysis casts light upon inherent incongruities that permeate customers' anticipations concerning personalised engagements, specifically necessitating the monitoring and utilising of geographical coordinates (Canhoto et al., 2023).

The comprehensive analysis of consumer reviews regarding the Louis Vuitton website and mobile applications through NLP had captivating findings. The research affirms that usefulness, ease of use, interactive communication, and personalisation can enhance consumers' attitudes and satisfaction. Notably, a satisfied consumer revealed the application's significant benefits and informative nature, and an unsatisfied consumer lamented its lack of usefulness and confusing interface. This finding indicates that a well-designed AI assistant and how the service is valuable and easy to use has the potential to determine consumers' attitudes about the usage of AI assistants. These results are consistent with the literature (Hasan et al., 2021; Ashfaq et al., 2020; Zarouali et al., 2018).

Personalisation alludes to the AI shopping assistant's capacity to tailor services with the objective of meeting the specific needs and preferences of each customer (Chung et al., 2020; Srinivasan et al., 2002). The personalisation of AI shopping assistants' services is critical, considering that each consumer is unique (Hsu et al., 2021). A personalised approach entails offering the right services at the right time and to the right person (Chandra et al., 2022). The insights from the current study affirm those of Kaaniche et al. (2020), who demonstrate that customers are attracted to AI solutions that foster the personalisation of services. The findings align with the conceptual framework that personalisation contributes to the positive attitudes users and non-users develop towards AI assistants in e-commerce. Additionally, personalisation is tied to the TAM factors of perceived ease of use and usefulness (Kashive et al., 2018). Personalised AI assistant services imply that individuals can customise their interactions with the system, which enhances the ease of use. The high-quality services fostered by personalisation reflect the perceived usefulness. These findings are important to demonstrate how a personalised approach creates value for the customer and the e-commerce companies using AI shopping assistants. Personalisation allows the AI assistants to develop constructive relationships with customers from different cultural backgrounds and enhances focus on their specific needs and interests, which enhances their satisfaction. Therefore, personalisation can enhance how AI shopping assistants are used to strategically market products by focusing on particular customer characteristics.

7.2.6 The Role of Attitude in the Intention to Use AI Assistants

The path "AT - > UI" demonstrates high coefficients for both non-users (β=0.80) and users (β=0.80), with highly significant t-values (non-users=19.52 and users=23.56) with significant p-value (<0.005), suggesting a strong and consistent impact of Attitude on User intension for both groups. Thus, the results mention that consumers' attitude positively influences the behavioural intention of using AI assistants as an e-commerce tool. This linkage is rooted in consumer behaviour's psychological and cognitive dimensions, elucidating the intrinsic interplay between attitude and behavioural intention in the context of AI-driven e-commerce tools. Primarily, a positive attitude signifies consumers' favourable perceptions, beliefs, and emotions towards AI assistants in the e-commerce milieu. Perceptions of usefulness, ease of use, trustworthiness, and personalisation of the AI assistant shape this disposition. When consumers view AI assistants as valuable aids that enhance shopping experiences, provide tailored recommendations, and streamline decision-making processes, they are more inclined to engage with these tools.

Furthermore, a positive attitude generates psychological comfort and reduces perceived risk among consumers. As they perceive AI assistants as competent, reliable, and capable of delivering satisfactory outcomes, apprehensions regarding technological glitches, inaccurate suggestions, or privacy breaches are assuaged. This psychological comfort increases the likelihood of consumers embracing AI assistants as integral components of their e-commerce journey.

The results of Hypothesis H6 are consistent with previous studies (Kasilingam, 2020; Zarouali et al., 2018). Moreover, it reveals that a positive attitude leads to accepting or using an application or any new technology, which in this study is AI (Mullins & Cronan, 2021). Hence, attitudes represent individuals' overall evaluation, feelings, and beliefs about a particular technology. Consumers who develop positive attitudes toward AI assistants are likelier to perceive them as valuable, enjoyable, and beneficial. Positive attitudes create a sense of perceived usefulness and ease of use, which are important determinants of consumer intention to adopt and utilise AI assistants (Jo, 2022). On the other hand, negative attitudes can create fear or distrust, leading to a decreased intention to use AI assistants (Hornung & Smolnik, 2022). Therefore, understanding and influencing consumer attitudes through effective communication, education, and addressing concerns play a crucial role in promoting the adoption and acceptance of AI assistants in the consumer market. Meanwhile, when individuals have a positive behavioural intention toward AI assistants, it suggests that they are inclined to adopt and utilise the technology in their daily lives. This intention often translates into actual usage behaviour, as individuals tend to follow through on their intentions and act accordingly. Nonetheless, studying behavioural intention provides valuable insights into consumers' adoption and utilisation patterns, aiding in developing and improving AI assistants to better cater to users' needs and preferences. Henceforth, it is discerned that the behavioural intention shall ascertain the subsequent utilisation conduct (Davis, 1989). This notion finds empirical substantiation in the work of Purwanto and Loisa (2020), who observed a constructive and statistically substantial association between mobile banking systems and the eventual manifestation of utilisation conduct about banking systems. Further, a congruent observation was articulated by Tandi Lwoga and Questier (2014), wherein the behavioural intent underlying the engagement with communication systems emerged as a reliable predictor of subsequent effective usage behaviour.

Moon and Kim (2001) describe attitude as the feelings experienced by an individual when using AI shopping assistants. According to Jain and Weiten (2020), attitude is a psychological construct that reflects the beliefs and feelings individuals relate to particular products or services. Therefore, attitude is associated with behavioural intentions and decision-making. Zarouali et al. (2018) describe usage intentions as the willingness to use and continue using the AI shopping assistants. A positive attitude towards the use of AI shopping assistants emerges from the customers' fulfilment with the services. This aligns with TAM in that the positive attitude is an outcome of psychological conceptualisations regarding the perceived ease of use and usefulness. As highlighted in the conceptual framework, attitude is a construct of the cumulative impact the TAM factors, interactive communication, and personalisation have on the customers' experience (Pei & Zhenxiang, 2006). Although TAM does not focus on cultural influences, the inclusion of interactive communication and personalisation in the conceptual framework affirms that cultural differences can influence the attitude and intention to adopt and continue using AI assistants. The findings highlight the subjective nature of attitude and intentions as psychological and cognitive constructs. Therefore, individuals from different cultural backgrounds and experiences might express different attitudes and intentions to use AI assistants.

7.2.7 Comparison of Western and Eastern Consumers

The results present the differences in the mean values (Western - Eastern) for various paths in a multi-group analysis of attitudes and intentions related to AI usage. The p-values for both one-tailed and two-tailed tests are reported to assess the statistical significance of these differences. The findings reveal no statistically significant differences between Western and Eastern consumers' attitudes and intentions towards using AI assistants across the examined paths. Specifically, for paths AT -> UI, ICOM -> AT, PE -> AT, PE -> PU, PERS -> AT, and PU -> AT, the differences in means are not substantial enough to warrant statistical significance, as evidenced by the p-values exceeding conventional significance thresholds ($p > 0.05$). This suggests that the observed variations between Western and Eastern consumers' responses are likely due to random fluctuations or inherent similarities between the two groups in the context of AI assistant attitudes and intentions rather than meaningful cultural or regional distinctions.

In Western cultural contexts, distinguished by their propensity for individualism (Kim et al., 2022; Kim, 1994) and emphasis on autonomous decision-making, an environment conducive to swift technology assimilation tends to prevail. This trend is driven by congruence between adopting technological innovations and notions of self-expression and individual efficacy (Leidner & Kayworth, 2006). Conversely, a more circumspect stance towards integrating technology is often observed within Eastern cultural milieus, characterised by a prominent emphasis on collectivism and the pursuit of social harmony (Triandis, 2015). In such settings, stability and adherence to tradition hold elevated significance, manifesting as a discernible predilection for measured and deliberate technology incorporation, as underscored by the insights of Erez et al. (1993). Consequently, Western and Eastern consumers exhibit similarities in accepting and adopting AI assistants. A question can arise as to why and how both cultures have similar attitudes and intentions. There may be different reasons. Firstly, advancements in technology, such as the widespread availability of smartphones and the Internet, have facilitated the dissemination of information and global trends. As a result, consumers across different cultures have been exposed to similar experiences and influences, leading to shared beliefs and attitudes towards emerging technologies like AI assistants. Secondly, the globalisation of markets and the interconnectedness of economies have contributed to the diffusion of cultural values and consumer behaviours. Western and Eastern cultures have experienced increased cultural exchange and interaction, which has led to adopting similar beliefs and preferences, including using AI assistants. Moreover, the functionality and benefits offered by AI assistants are often universal and independent of cultural differences. AI assistants provide users convenience, efficiency, and personalised experiences regardless of their cultural background. These shared advantages contribute to the similarity in beliefs regarding their utilisation among Western and Eastern consumers. Furthermore, the results of Gillespie et al. (2023) reveal a consistent trend indicating reduced trust, increased ambivalence, and less favourable perceptions of AI in Western nations. Additionally, individuals in Singapore exhibit relatively lower levels of trust, ambivalence, and positive attitudes towards AI, albeit to a lesser degree (Gillespie et al., 2023). The findings in the current study show that the primary factors lack a significant influence on customer attitudes and intentions to use AI assistants in e-commerce. These insights contradict the sentiment expressed by Jiang et al. (2022) based on SET that social interactions tend to influence how individuals interact with AI shopping, considering the lack of a significant difference in the attitudes and intentions emerging in the cross-cultural context. Nevertheless, the findings affirm that the primary factors influencing the intention to use AI assistants prevail across cultures. The insights are inherent in demonstrating that the technological features and alignment of the AI assistants with the customer needs and preferences supersede cultural dimensions in e-commerce.

7.2.8 Mixed-Method Findings

This section discusses the mixed method findings of quantitative and qualitative studies of this research. Firstly, consumers who have an increased perception of AI assistants' usefulness exhibit a correspondingly favourable disposition toward their integration within e-commerce applications (Balakrishnan & Dwivedi, 2021). This alignment is substantiated by qualitative insights, wherein consumers manifest appreciation for the salient attributes of these AI entities, including the provision of illustrative imagery, real-time updates, and expeditious responsiveness during online shopping interactions (Xiong, 2022). Evident from the synthesis of quantitative and qualitative facets is a harmonious convergence, wherein the quantitative evidence corroborates the affirmative impact of perceived usefulness on attitudes. In contrast, the qualitative revelations amplify this effect by elucidating the intricate utility dimensions illuminated by consumers' experiential encounters.

The findings from this study affirm the perception that the perceived ease of use and usefulness have a positive correlation with the altitude and intention to adopt and continue using AI assistants in e-commerce. Integration of the qualitative and quantitative findings demonstrates that cultural differences that exist among Western and Eastern cultures have no significant impact on the perceived ease of use and usefulness. Therefore, cultural differences have no impact on the attitude and intention to adopt and use AI shopping assistants. However, the personalisation of AI assistant services is essential in enhancing customer satisfaction and creating value for the company and customers in their shopping experience.

The dimension of ease of use unfurls a comparable narrative, as consumers attributing inherent ease to using AI assistants manifest an inherently positive stance towards their adoption (Bawack & Desveaud, 2022). This alignment finds reinforcement in the qualitative domain, where online shoppers extol the virtues of streamlined product searches, visual presentations, personalised recommendations, navigational fluidity, accessibility enhancements, and interactive engagements that embellish their virtual shopping sojourns. The quantitative assessment underscores this synergy by affirming the affirmative influence of ease of use on consumer attitudes, and the qualitative expositions validate this trajectory by accentuating the pivotal constituents of user-friendliness through the lens of consumers' lived encounters.

Personalisation, another cardinal dimension, emanates as a pivotal determinant, positing that AI assistants' proclivity to furnish bespoke experiences begets a correspondingly elevated proclivity of consumers toward their utilisation (Kumar et al., 2019). This contention is buttressed by qualitative accounts wherein consumers express contentment with personalised product offerings and pertinent suggestions grounded in their unique requisites. This qualitative semblance resonates harmoniously with the quantitative substrate, wherein it becomes palpable that personalisation accrues as a salient contributor to fostering favourable consumer attitudes. The qualitative strands further support this standpoint by accentuating the conspicuous resonance engendered by the discerning alignment of AI-enabled personalisation and consumers' bespoke expectations.

The findings on personalisation in the current study align with the conceptualisation that a tailored approach to interacting with customers leads to higher satisfaction and positive attitudes and intention to continue using AI assistants. Additionally, the study demonstrates that personalisation is valued by customers from all cultures, which implies that it is a factor that should be integrated into the AI assistants adopted in e-commerce. Such considerations can contribute to enhanced marketing capabilities and a driver for competitive advantage in the dynamic business environment characterised by a highly diverse customer base.

Communication, the final dimension under scrutiny, accentuates AI assistants' interactive conversational adeptness in shaping consumers' predisposition toward their incorporation (Ho, 2021). As discerned through the qualitative lens, consumers evince distinct gratification from sophisticated, affable, and efficient communication throughout their virtual interactions. The quantitative landscape substantiates this panorama, delineating that interactive communication has substantive sway over consumers' attitudes. The qualitative dimension dovetails elegantly with this purview, unravelling the intricate interplay between communication styles and customer satisfaction, converging with the quantitative findings in a harmonious confluence. Quantitative and qualitative strands interlace in the tapestry of these dimensions, imbuing the study's findings with robust and multi-dimensional validation. The findings in the current study show a consensus that interactive communication is inherent in developing altitude and intention to use AI shopping assistants. In the cross-cultural context, interactive communication enhances the perceptions about the ease of use and usefulness of AI assistants. These insights show that interactive communication is considered essential by all consumers. Therefore, enhancing the interactive communication capabilities of the AI assistants can contribute to the positive attitudes and intention to use among all customers. The communication should be categorised by alignment of the language with the customers' cultural background for all users to engage with the AI assistants and the companies effectively gain valuable feedback that can be used for continuous improvement of the technologies and offerings.

7.4 Contribution and Implication for this Study

7.4.1 Theoretical Implications

In technological adoption and human-computer interaction, the interplay between usefulness, ease of use, interactive communication, personalisation with AI, attitude towards AI usage, and behavioural intention to use AI assistants reveals a complex web of theoretical implications (Chen et al., 2022). The finding that perceived usefulness positively influences users' and non-users' attitudes towards AI usage has significant theoretical implications. This finding is consistent with TAM and related behavioural theories, affirming the crucial role of perceived usefulness in shaping individuals' attitudes toward adopting new technologies. It underscores the universality of this construct, suggesting that perceptions of a technology's practical benefits not only influence current users' attitudes but also impact how attitudes develop among those unfamiliar with the technology. This suggests that efforts to enhance perceived usefulness through research or highlighting utilitarian advantages could effectively foster positive attitudes among existing users and mitigate skepticism or resistance among non-users. These insights contribute to a deeper understanding of technology adoption dynamics.

Furthermore, the finding that perceived ease of use positively influences users' attitudes towards using AI in e-commerce holds significant theoretical implications. This suggests that

AI systems' perceived simplicity and user-friendliness play a pivotal role in shaping individuals' attitudes, transcending the distinction between those familiar with the technology and those not. This emphasises the critical role of developing intuitive and accessible AI interfaces to improve attitudes and adoption across diverse user groups. It underscores the potential to reduce entry barriers and enhance overall acceptance of AI-driven e-commerce platforms (Balakrishnan & Dwivedi, 2024). In addition, theoretical implications arise when exploring the relationship between usefulness and ease of use and consumer attitudes toward AI assistants, shedding light on how these factors interact and influence one another. Here, some of these theoretical implications are discussed. First, this study makes a valuable contribution to the existing body of research on AI technology. Second, this research builds upon existing studies on technology acceptance by exploring novel external factors that enhance the effectiveness of AI assistants, thereby contributing to the advancement of AI literature (Istiqomah & Alfansi, 2024). Moreover, it is central to this intricate framework regarding AI assistants' usefulness and ease of use, which act as foundational pillars shaping their perceptions and subsequent behaviours (De Cicco et al., 2020). Perceived usefulness, reflecting the extent to which individuals believe AI assistants enhance their efficiency and effectiveness, can be seen as a driving force behind the willingness to engage with such technology (Zhang et al., 2021). Similarly, perceived ease of use, encompassing the perceived usefulness of integrating AI assistants into daily routines, directly influences users' attitudes and adoption decisions (Uzir et al., 2023).

Moreover, AI assistant characteristics amplify users' engagement and satisfaction, particularly in interactive communication and personalisation (Alkhateeb et al., 2023). The degree to which AI assistants facilitate seamless, human-like interactions plays a vital role in mitigating the psychological gap between users and machines. By employing natural language processing and context comprehension, AI assistants foster meaningful and fluid dialogues, enhancing the overall user experience. Furthermore, personalisation, tailoring interactions and recommendations based on individual preferences and behaviour history, adds another layer of appeal (Dwivedi et al., 2021). This adaptation fosters a sense of AI assistants being personalised companions, aligning with users' unique needs and desires, consequently solidifying positive attitudes and behavioural intentions.

Additionally, attitude, a pivotal psychological construct, mediates behavioural intentions (Acikgoz et al., 2023). Favourable attitudes stemming from perceived usefulness, ease of use, interactive communication, and personalisation are precursors to users' propensity to integrate AI assistants into their lives (Ashrafi & Easmin, 2023). Furthermore, the attitude-behaviour relationship is manifested in the behavioural intention to use AI assistants. Individuals' intent to engage with AI technology is influenced by their perception of its value, compatibility with their needs, and the anticipation of a gratifying experience (de Andrés-Sánchez & Gené-Albesa, 2023). The intention signifies the users' inclination to embrace AI assistants and reflects their proactive approach towards incorporating them as indispensable tools. This dynamic interplay reinforces those individual attitudes, fortified by perceived utility and ease, which are pivotal determinants of AI adoption trajectories.

Finally, the lack of support for the hypothesised difference between Western and Eastern consumers' attitudes and intentions towards using AI assistants bears essential theoretical implications. While prior research has often emphasised cultural variations in technology acceptance, the present model's failure to uncover such disparities suggests a need for re-evaluation. Western societies, marked by their individualistic orientation (Kim et al., 1994) and emphasis on self-reliance, commonly cultivate a milieu conducive to swift technology assimilation, given its consonance with concepts of self-actualisation and pragmatic efficacy (Leidner & Kayworth, 2006). Conversely, Eastern cultures, notable for their emphasis on collectivism and communal harmony (Triandis, 2015), often exhibit a cautious attitude towards technological integration (Erez et al., 1993). This outcome challenges assumptions that cultural factors inherently lead to divergent perceptions of AI technology, highlighting the significance of individual-level variables and context-specific influences. These results underscore the complex interplay of psychological, socioeconomic, and situational factors in shaping attitudes and intentions towards AI across diverse consumer groups, urging researchers to adopt a more nuanced and holistic approach when examining cross-cultural technology adoption patterns.

The revelations emerging from this study demonstrate the need to expand the TAM model to cover the diverse aspects of technology adoption in the modern day. Although TAM is valuable in assessing the primary factors of perceived ease of use and usefulness in shaping the attitude and intention to use, the model needs to expound on the underlying factors that influence decision-making. Integrating a cultural dimension can enhance how TAM is employed as a theoretical basis for investigating a diverse population of technology users. A cultural dimension can help to establish the differences among people and the factors that align their interests in a particular technology with their characteristics. Suggestively, the TAM can be improved by highlighting how culture is essential in shaping the psychological and cognitive factors that drive attitude and intention to use a particular technology.

In conclusion, converging AI assistant attributes, attitudes, and behavioural intentions establish a multifaceted paradigm that shapes the landscape of AI technology assimilation. Recognising the intricate links between these elements is indispensable for designing effective strategies to encourage AI adoption. Developers must cultivate intuitive interfaces that enhance perceived ease of use while integrating interactive communication and personalisation, ensuring positive experiences. Simultaneously, fostering positive initial experiences and streamlined onboarding processes can cultivate favourable attitudes that steer individuals towards embracing AI technology. As AI continues its transformative march, a nuanced understanding of these theoretical implications will be instrumental in navigating the complex terrain of human-AI interaction.

7.4.2 Practical Implications

The study's findings regarding AI’s usefulness and ease of use, coupled with AI assistant characteristics such as interactive communication and personalisation, have significant practical implications. By considering the practical implications outlined below, businesses can better navigate cultural diversity and tailor their AI assistant offerings to effectively engage and meet the needs of diverse consumer markets.

Firstly, businesses should focus on enhancing AI assistants' functionality, aligning them with users' perceptions of usefulness and ease of use to drive adoption. In addition, marketing managers have the opportunity to enrich customers' experience through the introduction of advanced AI assistants that can effectively provide customer support. The research findings demonstrate that the attributes of AI assistants, particularly interactive communication, significantly impact consumers' attitudes towards these AI assistants. The finding implies that consumers are likely to use and adapt this AI application regularly, and managers can gain advantages from understanding their customers’ chat preferences and integrating various elements of communication style design, such as language, context, empathy, and friendliness. Managers must recognise the significance of aligning communication styles with customer preferences to maximise the application's utilisation and ensure its success in the market. Understanding consumers' chatting styles can influence user experience design to embed personalised chat options to match customer requirements or personalities. Implementing personalised conversation options offers consumers greater control over their interactions, empowering them to modify language preferences, adjust their tone of voice, and receive tailored recommendations. By incorporating these features, AI assistants enhance the perceived value for users, resulting in an improved overall experience. This customisation enables brands to establish stronger customer connections, enhancing online customer experience and satisfaction. Furthermore, these adaptations contribute to a more seamless and meaningful brand-consumer interaction, fostering increased loyalty and brand affinity. Consequently, integrating personalised conversation options benefits consumers by giving them a sense of agency. It serves as a valuable tool for brands seeking to optimise their customer experiences in the digital realm.

Second, this study also provides insights for AI developers; for instance, AI assistant developers can enhance their products by prioritising prompt and efficient responses to customer inquiries while also implementing filtering mechanisms to deliver more relevant and personalised content. This improvement is likely to have a more significant impact on the long-term viability of an information system. Developers need to recognise and capitalise on such opportunities to optimise user experiences and achieve better outcomes in AI development. Moreover, changing attitudes towards AI assistants will profoundly impact consumers' inclination to utilise AI assistants for communicating with a brand through e-commerce platforms. This positive and transformative change is critical because firms across nearly every business sector (e.g., retailing, manufacturing, healthcare, and financial) progressively allocate more resources to their technology investments. The imperative drives these organisations to accomplish various objectives (Grewal et al., 2020) and for financial savings. Additionally, consumers may interact more with companies by embracing AI assistants as a communication medium, resulting in improved customer experiences and more convenience. This positive trend is a critical opportunity for organisations to harness new technology and successfully communicate with their target audience, promoting growth and competitive advantage in the market. Furthermore, AI-based assistants may offer a cost-effective way to increase and seamlessly scale up AI interactions with customers across multiple platforms (Grewal et al., 2020). The successful implementation of chatbots and virtual assistants may increase communication effectiveness and improve customer support productivity by integrating AI capabilities (Chong et al., 2021; Clark, 2020). Furthermore, the lack of supported differences in attitudes and intentions towards using AI assistants between Western and Eastern consumers suggests significant practical implications. Organisations developing AI technologies and services can adopt a more standardised approach in designing and marketing AI assistants, focusing on universal user needs and preferences rather than tailoring extensively to regional differences. This can lead to cost savings in development and marketing efforts, allowing for more efficient resource allocation. However, it is crucial to remain vigilant and continue monitoring potential regional shifts in attitudes and preferences, as cultural, socioeconomic, and technological factors may evolve, potentially altering the dynamics between Western and Eastern consumer segments in the future.

The insights emerging from the current study demonstrate the need for a strategic approach to designing and implementing AI technologies in e-commerce that involves gathering adequate data on the target customer base. Although there is no significant statistical difference between Western and Eastern cultures in the primary factors that influence attitudes and intentions to adopt AI shopping assistants, the relevance of interactive communication and personalisation demonstrates the need to focus on understanding the customer. Therefore, technology developers and the management of e-commerce businesses require input from customers in the development of AI solutions to enhance the capacity to communicate. For instance, understanding the use of language among the target customers can improve the flow of information, facilitating valuable feedback for the company while improving the customer experience by meeting their specific needs and preferences. The findings show that there are opportunities to increase the societal acceptance of AI technologies among e-commerce consumers. Non-users can be transformed into users by targeting the psychological and cognitive factors that influence the attitudes and intentions to use a particular technology. Such achievements entail focusing on the technology features that enhance the perceived ease of use and usefulness. This can be achieved by offering the relevant information to enhance the customer skills and knowledge concerning AI assistants and developing them to respond to the diverse needs of experienced and new users. Leveraging the large volumes of data available in the organisational and third-party platforms can improve the AI assistants by integrating cultural sensitivity in responding to customer needs and preferences. However, ethical considerations should be upheld when using customer data from within and outside the company, considering the impact data breaches and privacy violations can have on customers and the companies involved.

7.5 Conclusion

Technology now provides online assistance in e-commerce through AI assistants for global consumers. This research undertook an interdisciplinary approach by conducting two distinct studies. Firstly, an empirical survey questionnaire was employed to examine the relationships among the constructs of the proposed model. Next, the second study used ML and NLP techniques to analyse customer reviews and achieve the objective of eliciting supportive insights. The survey data analysis employs various statistical techniques, including primary descriptive analyses, multivariate analysis, and PLS-SEM utilising SPSS and SmartPLS (Version 4) software programs. Through these analyses, the survey validates an empirical model that effectively captured the interrelationships among the constructs of the conceptual model and formulated a hypothesis. Subsequently, the second stage of the research focuses on conducting the NLP analysis, aligning with the study's objectives. The study findings indicate that the usefulness, interactive communication, and personalisation were well supported by the users and non-users of AI assistants, and these factors positively influenced the attitudes, while ease of use was not supported by non-users. In addition, attitude positively impacts usage intentions to continue using AI assistants among users and non-users. Moreover, there were no significant differences exist in the relationships among the primary factors influencing the intention to utilise AI assistants in e-commerce when comparing Western and Eastern cultural groups. Furthermore, these findings emphasise the importance of e-commerce users carefully selecting a suitable characteristic for AI assistants during development to ensure customer satisfaction. In conclusion, this research contributes to the understanding of AI assistant usage. It provides practical insights for developing AI virtual assistants, providing inspiration for future researchers in this emerging field. In addition, the collaborative efforts of AI developers, researchers, and users can redefine the boundaries of human-computer interaction and lead us into an era where AI assistants are seamlessly integrated into the fabric of daily existence. As the potential of AI continues to unfold, understanding and adapting to these dynamics will be pivotal in charting the course of technology adoption and its impact on society.

7.6 Limitations and Direction for Future Research

Although this thesis makes a significant contribution to AI assistant adoption and its usage in e-commerce, some limitations should be noted for future research. The following points summarise these limitations and provide recommendations for future research.

- There was a limitation regarding the focus of this study on specific factors that limited the ability to explore other factors of AI capabilities that could be a significant influencer on the attitudes towards AI assistants. Future studies could explore the impact of other AI assistants' capabilities, like proactive assistance and advanced problem-solving, that might influence consumers' beliefs and attitudes towards using AI assistants. Given the focus of this study on the perspectives of users and non-users, however, external factors of consumers' demographics, such as age and gender, may impact the adoption of AI assistants. Future studies could investigate how a specific group of age or gender responds to the AI assistant interaction and explore their differences and similarities towards their intention to use this technology.

- There was a limitation regarding the sampling and sample size. This study has variations in sample sizes between the quantitative and qualitative components, which could affect the balance of insights derived from each component. Additionally, the focus on Louis Vuitton e-commerce applications in the qualitative study might limit the generalizability of findings to a broader range of e-commerce platforms. Future studies could include a comparable sample size and consider a wider selection of e-commerce platforms to ensure a more balanced integration of insights and enhance the generalizability of findings. Also, a limitation of the quantitative study in relation to dividing the sample into Western and Eastern cultures based on the regions of the responses. Future research could explore more country-specific studies to deepen understanding of cultural influences on AI assistant use. The data from the two countries can show how people from different places think and act differently. It helps compare the users' differences that affect their attitudes and actions. But to understand global trends better for using AI technologies, including more countries would be helpful. The use of IP address in sampling lacked accuracy and led to assumptions that participants' location reflected their cultural background, ignoring that they might be using VPN proxies or might have travelled or moved to their current locations. Future studies should focus on the experience and attitude that emerge from users, factoring in the diversity in demographic backgrounds to establish how social factors, norms, and beliefs affect their perceptions towards AI assistants. Therefore, future studies could purposefully select a diverse set of countries from both Western and Eastern regions and use alternative sampling techniques that ensure accuracy in the characteristics of the participants, considering that the IP address approach used in this study did not guarantee that individuals were from their respective cultures.

- Another limitation of the study was the focus on extending the TAM model, limiting the ability to adopt other models and explore other external factors that may have also been significant for fostering AI assistant adoption in e-commerce. Future studies may explore alternative research models, such as a combination of the TRA and cultural dimensions theories, to delve into the cultural factors influencing the usage behaviour of AI assistants. Further research could also focus on media influence, peer opinions, or marketing campaigns promoting AI assistant usage.
- From a research context point of view, in this study, the main domain is e-commerce. Further investigations in AI applications have the potential to expand upon discoveries by examining additional factors that influence the intention to utilise AI assistants in various contexts. For instance, exploring the impact of such predictors in education or healthcare can enhance the understanding of this phenomenon.
- There was also a limitation regarding the two examples of AI assistant interaction simulations that were presented to participants, which limited the ability to obtain in-depth perceptions regarding the usage of AI assistants. Future studies can explore incorporating participants' real-time interaction with AI assistants, which would provide valuable insights into the evolving interests of consumers during such interactions. Furthermore, it will also help identify specific pain points and outcomes in live chats across varying timeframes. Interviewing 10-15 customers should be conducted to give deeper explanations that match the online review data. This approach will provide a better understanding of customer experiences and opinions, allowing for the identification of deep insights that complement the findings of the quantitative data. These interviews can also provide detailed feedback on user satisfaction, areas needing improvement, and suggestions for making AI assistants better.

7.7 Chapter Summary

This chapter offers an in-depth analysis of the research findings and provides recommendations based on those findings. It begins by revisiting the research aim and the research questions. Following that, it presents a discussion of the study's findings. The theoretical and practical implications of the study's findings are discussed. Finally, this chapter concluded by identifying the study's limitations and providing recommendations for future research.

References

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms. Education and Information Technologies, 28(11), 15381-15413.

Abdalla, M. M., Oliveira, L. G. L., Azevedo, C. E. F., & Gonzalez, R. K. (2018). Quality in qualitative organizational research: Types of triangulation as a methodological alternative. Administração: ensinoe pesquisa, 19(1).

AbuShawar, B., & Atwell, E. (2015). ALICE chatbot: Trials and outputs. *Computación y Sistemas*, *19*(4), 625-632.

Acikgoz, F., Perez-Vega, R., Okumus, F., & Stylos, N. (2023). Consumer engagement with AI-powered voice assistants: A behavioural reasoning perspective. *Psychology & Marketing*.

Adiwardana, D., Luong, M. T., So, D. R., Hall, J., Fiedel, N., Thoppilan, R., ... & Le, Q. V. (2020). Towards a human-like open-domain chatbot. *arXiv preprint arXiv:2001.09977*.

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427-445.

Aguinis, H., Villamor, I., & Ramani, R. S. (2021). MTurk research: Review and recommendations. Journal of Management, 47(4), 823-837.

Aguinis, H., Villamor, I., & Ramani, R. S. (2021). MTurk Research: Review and Recommendations. Journal of Management, 47(4), 823–837.

Ajzen, I. (2020). The theory of planned behaviour: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314-324.

Ajzen, I., and Fishbein, M. (1980). Understanding attitudes and predicting social behaviour. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Ajisoko, P. (2020). The use of Duolingo apps to improve English vocabulary learning. *International Journal of Emerging Technologies in Learning (iJET)*, *15*(7), 149-155.

Ahmed, A., Aziz, S., Khalifa, M., Shah, U., Hassan, A., Abd-Alrazaq, A., & Househ, M. (2022). Thematic analysis on user reviews for depression and anxiety chatbot apps: Machine learning approach. *JMIR Formative Research*, *6*(3), e27654.

Akhtar, M., Neidhardt, J., & Werthner, H. (2019). The potential of chatbots: analysis of chatbot conversations. In *2019 IEEE 21st Conference on Business Informatics (CBI)* (Vol. 1, pp. 397-404). IEEE.

Akour, I., Alnazzawi, N., Alshurideh, M., Almaiah, M. A., Al Kurdi, B., Alfaisal, R. M., & Salloum, S. (2022). A Conceptual Model for Investigating the Effect of Privacy Concerns on E-Commerce Adoption: A Study on United Arab Emirates Consumers. *Electronics*, *11*(22), 3648.

Ali, I. (2020). The COVID-19 pandemic: Making sense of rumour and fear: Op-ed. *medical anthropology*, *39*(5), 376-379.

Alduaij, M. (2019). 'Employing the technology acceptance model to explore the trends of social media adoption and its effect on perceived usefulness and ease of use'. *Journal of Information Technology Management, 11*(2), 129–143.

Aldboush, H. H., & Ferdous, M. (2023). Building Trust in Fintech: An Analysis of Ethical and Privacy Considerations in the Intersection of Big Data, AI, and Customer Trust. *International Journal of Financial Studies*, *11*(3), 90.

Alnefaie, A., Gupta, D., Bhuyan, M. H., Razzak, I., Gupta, P., & Prasad, M. (2020). End-to-end analysis for text detection and recognition in natural scene images. In *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms. *Education and Information Technologies*, 1-33.

Alnefaie, A., Singh, S., Kocaballi, A. B., & Prasad, M. (2021). Factors Influencing Artificial Intelligence Conversational Agents Usage in the E-commerce Field: A Systematic Literature Review.

Altinok, D. (2018). An ontology-based dialogue management system for banking and finance dialogue systems—arXiv *preprint arXiv:1804.04838*.

Alves, T., Natálio, J., Henriques-Calado, J., & Gama, S. (2020). Incorporating personality in user interface design: A review. *Personality and Individual Differences*, *155*, 109709.

Alharahsheh, H. H., & Pius, A. (2020). A review of key paradigms: Positivism VS interpretivism. *Global Academic Journal of Humanities and Social Sciences*, *2*(3), 39-43.

Alkhateeb, M., Duné, E., & Akriem, E. (2023). The Impact of AI On Internal Communication Within an Organization: A Critical Examination of AI Adoption.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, *114*, 106548.

Ammenwerth, E. (2019). Technology acceptance models in health informatics: TAM and UTAUT. *Stud Health Technol Inform*, *263*, 64-71.

Amblee, N., & Bui, T. (2011). Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International journal of electronic commerce*, *16*(2), 91-114.

Antwi, S. K., & Hamza, K. (2015). Qualitative and quantitative research paradigms in business research: A philosophical reflection. *European journal of business and management*, *7*(3), 217-225.

Ansari, A., & Mela, C. F. (2003). E-customization. *Journal of marketing research*, *40*(2), 131-145.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. Computers in Human Behaviour, pp. 85, 183 –189.

Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI, we trust? Perceptions about automated decision-making by artificial intelligence. *AI & society*, *35*, 611-623.

Arthur, R. (2017). *Louis Vuitton Becomes Latest Luxury Brand to Launch a Chatbot*.

Argal, A., Gupta, S., Modi, A., Pandey, P., Shim, S., & Choo, C. (2018). Intelligent travel chatbot for predictive recommendation in echo platform. In *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 176-183). IEEE.

Aron, J. (2011). How innovative is Apple's new voice assistant, Siri?

Ashrafi, D. M., & Easmin, R. (2023). Okay, Google, Good to Talk to You… Examining the Determinants Affecting Users' Behavioral Intention for Adopting Voice Assistants: Does Technology Self-Efficacy Matter? *International Journal of Innovation and Technology Management*, *20*(02), 2350004.

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473.

Asenahabi, B. M. (2019). Basics of research design: A guide to selecting appropriate research design. *International Journal of Contemporary Applied Research*, *6*(5), 76-89.

Bahja, M. (2020). Natural language processing applications in business. *E-Business-higher education and intelligence applications*.

Baker, E., Al-Gahtani, S. S., and Hubona, G. S. (2007). The effects of gender and age on new technology implementation in a developing country: Testing the theory of planned behaviour (TPB*). Information Technology & People*, 20(4), 352-375.

Balakrishnan, J., & Dwivedi, Y. K. (2024). Conversational commerce: entering the next stage of AI-powered digital assistants. Annals of Operations Research, 333(2), 653-687.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Conversational commerce: entering the next stage of AI-powered digital assistants. *Annals of Operations Research*, 1-35.

Bavaresco, R., Silveira, D., Reis, E., Barbosa, J., Righi, R., Costa, C., ... & Moreira, C. (2020). Conversational agents in business: A systematic literature review and future research directions. *Computer Science Review*, *36*, 100239.

Bawack, R., & Desveaud, K. (2022). Consumer Adoption of Artificial Intelligence: A Review of Theories and Antecedents.

Bawack, R. E., Wamba, S. F., Carillo, K. D. A., & Akter, S. (2022). Artificial intelligence in E-Commerce: a bibliometric study and literature review. *Electronic markets*, *32*(1), 297-338.

Belli, G. (2008). Nonexperimental Quantitative Research. In: Lapan, S. D. & Quartaroli, M. T. (eds.) Research Essentials: An Introduction to Designs and Practices. Wiley.

Berger, V. W., & Zhou, Y. (2014). Kolmogorov–smirnov test: Overview. *Wiley statsref: Statistics reference online*.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 351-370.

Bhawiyuga, A., Fauzi, M. A., Pramukantoro, E. S., & Yahya, W. (2017). Design of an e-commerce chat robot for automatically answering customer questions. In *2017 International Conference on Sustainable Information Engineering and Technology (SIET)* (pp. 159-162). IEEE.

Billion, J., & Van den Abeele, D. (2007, June). ICOM: A Communication Framework for Interoperable European Railways. In *2007 7th International Conference on ITS Telecommunications* (pp. 1-6). IEEE.

Bland, J. M., & Altman, D. G. (1997). Statistics notes: Cronbach's alpha. *BMJ*, *314*(7080), 572.

Bono, R., Arnau, J., Alarcón, R., & Blanca, M. J. (2019). Bias, precision, and accuracy of skewness and kurtosis estimators for frequently used continuous distributions. *Symmetry*, *12*(1), 19.

Brandtzaeg, P. B., & Følstad, A. (2018). Chatbots: changing user needs and motivations. *interactions*, *25*(5), 38-43.

Bryman, A. & Bell, E. (2015). *Business Research Method's, 4th edition, OUP Oxford.*

Brill, T. M., Munoz, L., & Miller, R. J. (2022). Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. In The Role of Smart Technologies in Decision Making (pp. 35-70). Routledge.

Burnette, C. Blair, Jessica L. Luzier, Brooke L. Bennett, Chantel M. Weisenmuller, Patrick Kerr, Shelby Martin, Jillian Keener, and Lisa Calderwood. "Concerns and recommendations for using Amazon MTurk for eating disorder research." *International Journal of Eating Disorders* 55, no. 2 (2022): 263-272.

Cain, M. K., Zhang, Z., & Yuan, K. H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence, and estimation. *Behaviour research methods*, *49*, 1716-1735.

Canhoto, A. I., Keegan, B. J., & Ryzhikh, M. (2023). Snakes and ladders: unpacking the personalisation-privacy paradox in the context of AI-enabled personalisation in the physical retail environment. *Information Systems Frontiers*, 1-20.

Casula, M., Rangarajan, N., & Shields, P. (2021). The potential of working hypotheses for deductive exploratory research. *Quality & Quantity*, *55*(5), 1703-1725.

Cavana, R., Delahaye, B., & Sekeran, U. (2001). *Applied business research: Qualitative and quantitative methods*. John Wiley & Sons.

Cecez-Kecmanovic, D. (2005). Basic assumptions of the critical research perspectives in information systems. *Handbook of critical information systems research: Theory and application*, (19-46).

Çelik, H. E., & Yilmaz, V. (2011). Extending the technology acceptance model for adopting e-shopping by consumers in Turkey. *Journal of Electronic Commerce Research*, *12*(2), 152.

Cha, J. (2010). Factors affecting the frequency and amount of social networking site use: Motivations, perceptions, and privacy concerns. *First Monday*.

Cherrier, H. (2007). Ethical consumption practices: co-production of self-expression and social recognition. Journal of Consumer Behaviour: An International Research Review, 6(5), 321-335.

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalisation in personalised marketing: Trends and ways forward. *Psychology & Marketing*, *39*(8), 1529-1562.

Chandler, J., & Shapiro, D. (2016). Conducting clinical research using crowdsourced convenience samples. *Annual Review of Clinical Psychology,* 12(1), 53–81.

Chalmers, A. F. (1999). What is this thing called Science? (Vol. Third Edition). Open University Press

Chaves, A. P., & Gerosa, M. A. (2021). How should my chatbot interact? A survey on social characteristics in human–chatbot interaction design. *International Journal of Human–Computer Interaction*, *37*(8), 729-758.

Chen, H., Chan-Olmsted, S., Kim, J., & Mayor Sanabria, I. (2022). Consumers' perception of artificial intelligence applications in marketing communication. *Qualitative Market Research: An International Journal*, *25*(1), 125-142.

Chen, J. S., Le, T. T. Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, *49*(11), 1512–1531.

Chawla, N., & Kumar, B. (2022). E-commerce and consumer protection in India: the emerging trend. *Journal of Business Ethics*, *180*(2), 581-604.

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts. *Journal of Product & Brand Management*, *31*(2), 252-264.

Cheng, M., & Jin, X. (2019). What do Airbnb users care about? An analysis of online review comments. *International Journal of Hospitality Management*, *76*, 58-70.

Chhabra, G., Vashisht, V., & Ranjan, J. (2017). A comparison of multiple imputation methods for data with missing values. *Indian Journal of Science and Technology*, *10*(19), 1-7.

Chi, T. (2018). Understanding Chinese consumer adoption of apparel mobile commerce: An extended TAM approach. *Journal of Retailing and Consumer Services*, *44*, 274-284.

Choudhury, A., Elkefi, S., & Tounsi, A. (2024). Exploring factors influencing user perspective of ChatGPT as a technology that assists in healthcare decision making: A cross-sectional survey study. PLoS One, 19(3), e0296151.

Choi, J., Lee, H. J., Sajjad, F., & Lee, H. (2014). The influence of national culture on the attitude towards mobile recommender systems. *Technological Forecasting and Social Change*, *86*, 65-79.

Choi, Y., Choi, M., Oh, M., & Kim, S. (2020). Service robots in hotels: understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing & Management*, *29*(6), 613-635.

Chi, O. H., Chi, C. G., Gursoy, D., & Nunkoo, R. (2023). Customers' acceptance of artificially intelligent service robots: The influence of trust and culture. International Journal of Information Management, 70, 102623.

Chi, O. H., Chi, C. G., Gursoy, D., & Nunkoo, R. (2023). Customer's acceptance of artificially intelligent service robots: The influence of trust and culture. *International Journal of Information Management*, *70*, 102623.

Chong, T., Yu, T., Keeling, D. I., & de Ruyter, K. (2021). AI chatbots on the service's frontline addressing the challenges and opportunities of the agency. Journal of Retailing and Consumer Services, 63, 102735.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587-595.

Clark, S. 5 Ways Chatbots Improve Employee Experience. 2020.

Clarizia, F., Colace, F., Lombardi, M., Pascale, F., & Santaniello, D. (2018). Chatbot: An education support system for students. In *Cyberspace Safety and Security: 10th International Symposium, CSS 2018, Amalfi, Italy, October 29–31, 2018, Proceedings 10* (pp. 291-302). Springer International Publishing.

Clark, L., Pantidi, N., Cooney, O., Doyle, P., Garaialde, D., Edwards, J., ... & Cowan, B. R. (2019, May). What makes a good conversation? Challenges in designing truly conversational agents. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-12).

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383.

Cornali, F., & Tirocchi, S. (2012). Globalization, education, information and communication technologies: what relationships and reciprocal influences?. Procedia-Social and Behavioral Sciences, 47, 2060-2069.

Conboy, K., Fitzgerald, G., & Mathiassen, L. (2012). Qualitative methods research in information systems: motivations, themes, and contributions. *European Journal of Information Systems*, *21*(2), 113-118.

Carcary, M. (2009). The research audit trial—enhancing trustworthiness in qualitative inquiry. *Electronic journal of business research methods*, *7*(1), pp11-24.

Dahiya, M. (2017). A tool of conversation: Chatbot. *International journal of computer sciences and engineering*, *5*(5), 158-161.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.

Daowd, A., Hasan, R., Eldabi, T., Rafi-ul-Shan, P. M., Cao, D., & Kasemsarn, N. (2021). Factors affecting eWOM credibility, information adoption and purchase intention on Generation Y: a case from Thailand. *Journal of Enterprise Information Management*, *34*(3), 838-859.

Dawadi, S., Shrestha, S., & Giri, R. A. (2021). Mixed-methods research: A discussion on its types, challenges, and criticisms. *Journal of Practical Studies in Education*, *2*(2), 25-36.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48, 24-42.

De Villiers, M. R. (2005, July). Three approaches as pillars for interpretive information systems research: development research, action research and grounded theory. In *Proceedings of the 2005 annual research conference of the South African Institute of Computer Scientists and Information Technologists on IT research in developing countries* (pp. 142-151).

De Cicco, R., Silva, S. C., & Alparone, F. R. (2020). Millennials' attitude toward chatbots: an experimental study in a social relationship perspective. *International Journal of Retail & Distribution Management*, *48*(11), 1213-1233.

de Andrés-Sánchez, J., & Gené-Albesa, J. (2023). Explaining Policyholders' Chatbot Acceptance with a Unified Technology Acceptance and Use of Technology-Based Model. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(3), 1217-1237.

de Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management*, *78*, 104042.

Ding, S., & Saunders, R. A. (2006). Talking up China: An analysis of China's rising cultural power and global promotion of the Chinese language. East Asia, 23(2), 3-33.

Drigas, A., Papanastasiou, G., & Skianis, C. (2023). The School of the Future: The Role of Digital Technologies, Metacognition and Emotional Intelligence. *International Journal of Emerging Technologies in Learning (Online)*, *18*(9), 65.

Duffett, R. (2020). The YouTube marketing communication effect on cognitive, affective and behavioural attitudes among Generation Z consumers. *Sustainability*, *12*(12), 5075.

Duijst, D. (2017). Can we improve the user experience of chatbots with personalisation? *Master's thesis. University of Amsterdam*.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

Elad, B. (2023). Online Shoppers Statistics by Country and Demographics. Enterprise Apps Today.

Elsholz, E., Chamberlain, J., and Kruschwitz, U. (2019). '*Exploring language style in chatbots to increase perceived product value and user engagement'.* Paper presented at the Proceedings of the 2019 Conference on Human Information Interaction and Retrieval.

Erez, M., & Earley, P. C. (1993). *Culture, self-identity, and work*. Oxford University Press, USA.

Espinoza, J., Crown, K., & Kulkarni, O. (2020). A guide to chatbots for COVID-19 screening at pediatric health care facilities. *JMIR public health and surveillance*, *6*(2), e18808.

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey. *International Journal of Bank Marketing*, *39*(2), 294-311.

Fan, S., Radford, J., & Fabian, D. (2016). A mixed-method research to investigate the adoption of mobile devices and Web2. 0 technologies among medical students and educators. BMC medical informatics and decision making, 16(1), 1-8.

Fakis, A., Hilliam, R., Stoneley, H., & Townend, M. (2014). Quantitative analysis of qualitative information from interviews: A systematic literature review. Journal of Mixed Methods Research, 8(2), 139-161.

Famili, A., Shen, W. M., Weber, R., & Simoudis, E. (1997). Data preprocessing and intelligent data analysis. Intelligent Data Analysis, 1(1), 3–23. https://doi.org/10.3233/IDA-1997-1102.

Faqih, K. M. (2022). Internet shopping in the Covid-19 era: Investigating the role of perceived risk, anxiety, gender, culture, and trust in the consumers' purchasing behaviour from a developing country context. *Technology in Society*, *70*, 101992.

Faqih, K. M. (2016). An empirical analysis of factors predicting the behavioral intention to adopt Internet shopping technology among non-shoppers in a developing country context: Does gender matter?. Journal of retailing and consumer services, 30, 140-164.

Fokina, M. (2022). *Online shopping statistics: E-commerce trends for 2022*. Tidio. https://www.tidio.com/blog/online-shopping-statistics/

Foroudi, P., Gupta, S., Sivarajah, U., & Broderick, A. (2018). Investigating the effects of smart technology on customer dynamics and customer experience. *Computers in Human Behavior*, *80*, 271-282.

Fernandes, A. (2020). Luxury Chatbots Helping Combat Slump in Sales During Pandemic. Retrieved from https://verloop.io/blog/how-luxury-chatbots-are-helping/.

Ferrario, A., & Nägelin, M. (2020). The art of natural language processing: classical, modern and contemporary approaches to text document classification. Modern and Contemporary Approaches to Text Document Classification.

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs—principles and practices. *Health services research*, *48*(6pt2), 2134-2156.

Fielding, N. G. (2012). Triangulation and mixed methods designs: Data integration with new research technologies. *Journal of mixed methods research*, *6*(2), 124-136.

Filieri, R., & Mariani, M. (2021). The role of cultural values in consumers' evaluation of online review helpfulness: a big data approach. *International Marketing Review*, *38*(6), 1267-1288.

Fishbein, M. (1979). A theory of reasoned action: some applications and implications.

Field, A. (2009), Discovering Statistics Using SPSS. Third Edition, SAGE Publications Ltd.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Sage.

Frank, B., Herbas-Torrico, B., & Schvaneveldt, S. J. (2021). The AI-extended consumer: technology, consumer, and country differences in the formation of demand for AI-empowered consumer products. *Technological Forecasting and Social Change*, *172*, 121018.

Foroughi, B., Iranmanesh, M., & Hyun, S. (2019). Understanding the determinants of mobile banking continuance usage intention. *Journal of Enterprise Information Management*.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics.

Følstad, A., & Brandtzaeg, P. B. (2020). Users' experiences with chatbots: findings from a questionnaire study. *Quality and User Experience*, *5*(1), 3.

Forkus, S. R., Contractor, A. A., Goncharenko, S., Goldstein, S. C., & Weiss, N. H. (2022). Online crowdsourcing to study trauma and mental health symptoms in military populations: A case for Amazon's Mechanical Turk (MTurk) platform. *Psychological trauma: theory, research, practice, and policy*.

Galetsi, P., Katsaliaki, K., & Kumar, S. (2023). Exploring benefits and ethical challenges in the rise of mHealth (mobile healthcare) technology for the common good: An analysis of mobile applications for health specialists. *Technovation*, *121*, 102598.

Ghazi, A. N., Petersen, K., Reddy, S. S. V. R., & Nekkanti, H. (2018). Survey research in software engineering: Problems and mitigation strategies. *IEEE Access*, *7*, 24703-24718.

Gjurković, M., & Šnajder, J. (2018). Reddit: A gold mine for personality prediction. In *Proceedings of the second workshop on computational modelling of people's opinions, personality, and emotions in social media* (pp. 87-97).

Gao, Y., & Liu, H. (2022). Artificial intelligence-enabled personalisation in interactive marketing: a customer journey perspective. *Journal of Research in Interactive Marketing*, (ahead-of-print), 1-18.

Gillespie, N., Lockey, S., Curtis, C., Pool, J., & Akbari, A. (2023). Trust in Artificial Intelligence: A global study.

Gnewuch, U., Morana, S., Adam, M., & Maedche, A. (2018). Faster is not always better: understanding the effect of dynamic response delays in human-chatbot interaction.

Goertzen, M. J. (2017). Introduction to quantitative research and data. *Library Technology Reports*, *53*(4), 12-18.

Go, E., & Sundar, S. S. (2019). Humanising chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*, 304-316.

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: A multidisciplinary perspective. Journal of the Academy of Marketing Science, 48(1), 1-8.

Grover, P., Kar, A. K., & Ilavarasan, P. V. (2019). Impact of corporate social responsibility on reputation—Insights from tweets on sustainable development goals by CEOs. *International journal of information management*, *48*, 39-52.

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational evaluation and policy analysis*, *11*(3), 255-274.

Goduka, N. (2012). From positivism to indigenous science: A reflection on world views, paradigms and philosophical assumptions. *Africa Insight*, *41*(4), 123-138.

Gümüş, N., & Çark, Ö. (2021). The Effect of Customers' Attitudes Towards Chatbots on their Experience and Behavioural Intention in Turkey. *Interdisciplinary Description of Complex Systems: INDECS*, *19*(3), 420-436.

Gupta, S., Borkar, D., De Mello, C., & Patil, S. (2015). An e-commerce website-based chatbot. *International Journal of Computer Science and Information Technologies*, *6*(2), 1483-1485.

Guetterman, T. C., & Fetters, M. D. (2018). Two methodological approaches to the integration of mixed methods and case study designs: A systematic review. *American Behavioral Scientist*, *62*(7), 900-918.

Guo, W., & Luo, Q. (2023). Investigating the impact of intelligent personal assistants on the purchase intentions of Generation Z consumers: The moderating role of brand credibility. Journal of Retailing and Consumer Services, 73, 103353.

Guzman, A. L. (2016). Making AI safe for humans: A conversation with Siri. In *Socialbots and their friends* (pp. 85-101). Routledge.

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A human–machine communication research agenda. *New media & society*, *22*(1), 70-86.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial management & data systems*, *117*(3), 442-458.

Harlap, A., Cui, H., Dai, W., Wei, J., Ganger, G. R., Gibbons, P. B., ... & Xing, E. P. (2016, October). Addressing the straggler problem for iterative convergent parallel ML. In *Proceedings of the seventh ACM symposium on cloud computing* (pp. 98-111).

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modelling: Rigorous applications, better results and higher acceptance. *Long range planning*, *46*(1-2), 1-12.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2010). Analysis using dependence techniques. *Multivariate Data Analysis, 7th ed. New Jersey: Prentice Hall*, 154-176.Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*.

Hasan, M. R., Maliha, M., & Arifuzzaman, M. (2019). Sentiment analysis with NLP on Twitter data. In *2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2)* (pp. 1-4). IEEE.
Hasan, A. A. T. (2022). Determinants of intentions to use the Foodpanda mobile application in Bangladesh: the role of attitude and fear of COVID-19. *South Asian Journal of Marketing*, *4*(1), 17-32.

Hasan, I., Ahmed, S. P., Ahmed, S. U., & Yousuf, T. B. (2021). Factors influencing users' willingness for online messaging services: a developing country perspective. *International Journal of Mobile Communications*, *19*(1), 75-98.

Hassanein, K., & Head, M. (2007). 'Manipulating perceived social presence through the web interface and its impact on attitude towards online shopping'. *International journal of human-computer studies*, 65(8), 689-708.
Harasis, A. A., Qureshi, M. I., & Rasli, A. (2018). Development of research continuous usage intention of e-commerce. A systematic review of literature from 2009 to 2015. *International Journal of Engineering & Technology*, *7*(2.29), 73–78.

Harrigan, M., Feddema, K., Wang, S., Harrigan, P., & Diot, E. (2021). How trust leads to online purchase intention founded in perceived usefulness and peer communication. *Journal of Consumer Behaviour*, *20*(5), 1297-1312.

Han, M. C. (2021). The impact of anthropomorphism on consumers' purchase decision in chatbot commerce. *Journal of Internet Commerce*, *20*(1), 46-65.

Hau, K. T., & Marsh, H. W. (2004). The use of item parcels in structural equation modelling: Non-normal data and small sample sizes. British Journal of Mathematical and Statistical Psychology, 57(2), 327-351.

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence-based nursing*, *18*(3), 66-67.

Hernani-Merino, M., Lazo, J. G. L., López, A. T., Mazzon, J. A., & López-Tafur, G. (2020). An international market segmentation model based on susceptibility to global consumer culture. *Cross Cultural & Strategic Management*, *28*(1), 108-128.

Hernández, B., Jiménez, J., & José Martín, M. (2011). Age, gender and income: Do they really moderate online shopping behaviour? *Online information review*, *35*(1), 113-133.

Hesham, F., Riadh, H., & Sihem, N. K. (2021). What have we learned about the effects of the COVID-19 pandemic on consumer behaviour? *Sustainability*, *13*(8), 4304.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International marketing review*, *33*(3), 405-431.

Hitchcock, J. H., & Nastasi, B. K. (2024). Advancing Cross-Cultural Research Through Mixed Methods Inquiry. Journal of Mixed Methods Research, 15586898241256207.

Hien, H. T., Cuong, P. N., Nam, L. N. H., Nhung, H. L. T. K., & Thang, L. D. (2018). Intelligent assistants in higher-education environments: the FIT-EBot, a chatbot for administrative and learning support. In *Proceedings of the 9th International Symposium on Information and Communication Technology* (pp. 69-76).

Hitlin, P. (2016) Research in the Crowdsourcing Age, a Case Study.

Holden, M.T. & Lynch, P. (2004). Choosing the appropriate methodology: Understanding research philosophy. The marketing review, 4(4), pp.397-409.

Hofstede, G. (1983). National cultures in four dimensions: A research-based theory of cultural differences among nations. *International studies of management & organization*, *13*(1-2), 46-74.

Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. *Online readings in psychology and culture*, *2*(1), 8.

Hong, Y. Y., Wan, C., No, S., & Chiu, C. Y. (2007). Multicultural identities. Handbook of cultural psychology, 323-345.

Ho, S. P. S., & Chow, M. Y. C. (2023). The role of artificial intelligence in consumers' brand preference for retail banks in Hong Kong. *Journal of Financial Services Marketing*, 1-14.

Ho, R. C. (2021). Chatbot for online customer service: customer engagement in the era of artificial intelligence. In *Impact of globalisation and advanced technologies on online business models* (pp. 16-31). IGI Global.

Hornung, O., & Smolnik, S. (2022). AI is invading the workplace: negative emotions towards the organisational use of personal virtual assistants. *Electronic Markets*, 1-16.

Hornbæk, K., & Hertzum, M. (2017). Technology acceptance and user experience: A review of the experiential component in HCI. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *24*(5), 1-30.

Hsu, S. H. Y., Tsou, H. T., & Chen, J. S. (2021). "Yes, we do. Why not use augmented reality?" customer responses to experiential presentations of AR-based applications. *Journal of Retailing and Consumer Services*, *62*, 102649.

Hsieh, J. Y., and Liao, P. W. (2011). Antecedents and moderators of online shopping behaviour in undergraduate students. Social Behavior and Personality: *An international journal*, 39(9), 1271-1280.

Huda, M. N. (2023). Analysis the Critical Factors of M-government Service Acceptance: An Integrating Theoretical Model between TAM and ECM. *Policy & Governance Review*, *7*(2), 109-124.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49, 30-50.

Huang, C. Y., Yang, M. C., Huang, C. Y., Chen, Y. J., Wu, M. L., & Chen, K. W. (2018). A chatbot-supported smart wireless interactive healthcare system for weight control and health promotion. In *2018*

IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) (pp. 1791-1795).

Hussain, S., Ameri Sianaki, O., & Ababneh, N. (2019). A survey on conversational agents/chatbot classification and design techniques. In *Web, Artificial Intelligence and Network Applications: Proceedings of the Workshops of the 33rd International Conference on Advanced Information Networking and Applications (WAINA-2019) 33* (pp. 946-956). Springer International Publishing.

Ikumoro, A. O., & Jawad, M. S. (2019). Intention to use intelligent conversational agents in e-commerce among Malaysian SMEs: an integrated conceptual framework based on tri-theories including unified theory of acceptance, use of technology (UTAUT), and TOE. International Journal of Academic Research in Business and Social Sciences, 9(11), 205-235.

Insider. (2020). Chatbot Market in 2021: Stats, trends, and Companies in the Growing AI chatbot industry. Retrieved from https://www.businessinsider.com/chatbot-market-stats-trends.

Istiqomah, P., & Alfansi, L. (2024). Navigating Style: Exploring the Influence of Perceived Benefit and Perceived Ease of Use on Attitude Towards Use in AI-Enhanced Fashion E-Commerce. Journal of Entrepreneurship and Business, 5(1), 1-14.

Ivankova, N. V., Creswell, J. W., & Stick, S. L. (2006). Using mixed-methods sequential explanatory design: From theory to practice. *Field methods*, *18*(1), 3-20.

Jain, S. P., & Weiten, T. J. (2020). Consumer psychology of implicit theories: A review and agenda. *Consumer Psychology Review*, *3*(1), 60-75.

Jain, S., Basu, S., Dwivedi, Y. K., & Kaur, S. (2022). Interactive voice assistants–Does brand credibility assuage privacy risks? *Journal of Business Research*, *139*, 701-717.

Jafari, A., Aly, M., & Doherty, A. M. (2022). An analytical review of market system dynamics in consumer culture theory research: Insights from the sociology of markets. *Journal of Business Research*, p. 139, 1261–1274.

Jantsch, L. B., & Neves, E. T. (2022). "Talking table" as a data integration strategy in mixed methods research. *Escola Anna Nery*, *27*.

Jannach, D., Manzoor, A., Cai, W., & Chen, L. (2021). A survey on conversational recommender systems. *ACM Computing Surveys (CSUR)*, *54*(5), 1-36.

Jan, I. U., Ji, S., & Kim, C. (2023). What (de) motivates customers to use AI-powered conversational agents for shopping? The extended behavioural reasoning perspective. *Journal of Retailing and Consumer Services*, *75*, 103440.

Jecker, N. S., & Nakazawa, E. (2022). Bridging East-West Differences in Ethics Guidance for AI and Robotics. *AI*, *3*(3), 764-777.

Jelavic, M., & Ogilvie, K. (2010). Knowledge management views in Eastern and Western cultures: an integrative analysis. *Journal of Knowledge Globalization*, *3*(2), 51-69.

Jervis, R. (2006). Understanding beliefs. *Political Psychology*, 27(5), 641–663.

Jeong, S. G., Hur, H. J., & Choo, H. J. (2020). The Effect of Fashion Shopping Chatbot Characteristics on Service Acceptance Intention-Focusing on Anthropomorphism and Personalization. *Journal of the Korean Society of Clothing and Textiles, 44* (4), 573–593.

Jiang, H., Cheng, Y., Yang, J., & Gao, S. (2022). AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behaviour. *Computers in Human Behavior*, *134*, 107329.

Jovic, D. (2020). Fascinating Chatbot Statistics. Retrieved from https://www.smallbizgenius.net/by-the-numbers/chatbot-statistics.

Jo, H. (2022). Continuance intention to use artificial intelligence personal assistant: type, gender, and use experience. *Heliyon*, *8*(9).

Kaaniche, N., Laurent, M., & Belguith, S. (2020). Privacy-enhancing technologies for solving the privacy-personalization paradox: Taxonomy and survey. *Journal of Network and Computer Applications*, *171*, 102807.

Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. The International Journal of Information and Learning Technology, 38(1), 1-19.

Kalia, A. K., Telang, P. R., Xiao, J., & Vukovic, M. (2017). Quark: a methodology to transform people-driven processes into chatbot services. In *Service-Oriented Computing: 15th International Conference, ICSOC 2017, Malaga, Spain, November 13–16, 2017, Proceedings* (pp. 53-61). Springer International Publishing.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280.

Kamalia, D., Djajadinata, M., Gunawan, F. H., & Gunadi, W. (2022). The role of hedonic motivation and FOMO on the Impulsivity of e-commerce users during COVID-19 Pandemics in Indonesia. In *Proceedings of the International Conference on Industrial Engineering and Operations Management Istanbul*.

Kaushik, V., & Walsh, C. A. (2019). Pragmatism as a research paradigm and its implications for social work research. *Social sciences*, *8*(9), 255.

Kautish, P., Purohit, S., Filieri, R., & Dwivedi, Y. K. (2023). Examining the role of consumer motivations to use voice assistants for fashion shopping: The mediating role of awe experience and eWOM. *Technological Forecasting and Social Change*, *190*, 122407.

Kaplan, B., & Duchon, D. (1988). Combining qualitative and quantitative methods in information systems research: a case study. *MIS Quarterly*, 571-586.

Kaplan, B., & Maxwell, J. A. (2005). Qualitative research methods for evaluating computer information systems. In *Evaluating the organisational impact of healthcare information systems* (pp. 30-55).

Keith, M. G., & McKay, A. S. (2024). Too Anecdotal to Be True? Mechanical Turk Is Not All Bots and Bad Data: Response to Webb and Tangney (2022). Perspectives on Psychological Science, 17456916241234328.

Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2022). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, 101925.

Kelly, A. E., & Palaniappan, S. (2023). Using a technology acceptance model to determine factors influencing continued usage of mobile money service transactions in Ghana. *Journal of Innovation and Entrepreneurship*, *12*(1), 34.

Kerrigan, M. R. (2014). A framework for understanding community collegesorganisationalal capacity for data use: A convergent parallel mixed methods study. *Journal of mixed methods research*, *8*(4), 341-362.

Kerlyl, A., Hall, P., & Bull, S. (2006). Bringing chatbots into education: Towards natural language negotiation of open learner models. In *International conference on innovative techniques and applications of artificial intelligence* (pp. 179-192).

Kelley, K., Clark, B., Brown, V., & Sitzia, J. (2003). Good practice in the conduct and reporting of survey research. *International Journal for Quality in Health Care*, *15*(3), 261-266.

Khan, S., & Rabbani, M. R. (2021). Artificial intelligence and NLP-based chatbot for Islamic banking and finance. *International Journal of Information Retrieval Research (IJIRR)*, *11*(3), 65-77.

Khanpour, H., Guntakandla, N., & Nielsen, R. (2016). Dialogue act classification in domain-independent conversations using a deep recurrent neural network. In *Proceedings of Coling 2016, the 26th International Conference on Computational Linguistics: Technical papers* (pp. 2012-2021).

Khan, E., Sperotto, A., van der Ham, J., & van Rijswijk-Deij, R. (2023). Stranger VPNs: Investigating the Geo-Unblocking Capabilities of Commercial VPN Providers. In International Conference on Passive and Active Network Measurement (pp. 46-68). Cham: Springer Nature Switzerland.

Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher*, *42*(8), 846–854. https://doi.org/10.1080/0142159X.2020.1755030.

Kim, J., & Gambino, A. (2016). Do we trust the crowd or information system? Effects of personalisation and bandwagon cues on users' attitudes and behavioural intentions toward a restaurant recommendation website. Computers in Human Behavior, 65, 369-379.

Kim, M., Ko, H., Choi, J., & Lee, J. (2023). FlumeRide: Interactive Space Where Artists and Fans Meet-and-Greet Using Video Calls. *IEEE Access*, *11*, 31594-31606.

Kim, J., Merrill Jr., K., & Collins, C. (2021). AI as a friend or assistant: The mediating role of perceived usefulness in social AI vs. functional AI. *Telematics and Informatics*, *64*, 101694.

Kim, Y. J., Toh, S. M., and Baik, S. (2022). Culture creation and change: Making sense of the past to inform future research agendas. Journal of Management.

Kim, M. S. (1994). Cross-cultural comparisons of the perceived importance of conversational constraints. *Human communication research*, *21*(1), 128-151.

Kim, M., & Chang, B. (2020). The effect of service quality on the reuse intention of a chatbot: Focusing on user satisfaction, reliability, and Immersion. *International Journal of Contents*, *16*(4), 1-15.

Klaus, P., & Zaichkowsky, J. L. (2022). The convenience of shopping via voice AI: Introducing AIDM. *Journal of Retailing and Consumer Services*, *65*, 102490.

Kline, R. B. (2023). *Principles and practice of structural equation modelling*. Guilford publications.

Kock, N. (2016). Hypothesis testing with confidence intervals and P values in PLS-SEM. *International Journal of e-Collaboration (IJeC)*, *12*(3), 1-6.

Kocielnik, R., Amershi, S., & Bennett, P. N. (2019, May). Will you accept an imperfect AI? Exploring designs for adjusting end-user expectations of AI systems. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1-14).

Kowatsch, T., Nißen, M., Shih, C. H. I., Rüegger, D., Volland, D., Filler, A., ... & Farpour-Lambert, N. (2017). Text-based healthcare chatbots supporting patient and health professional teams: preliminary results of a randomised controlled trial on childhood obesity. *Persuasive Embodied Agents for Behavior Change (PEACH2017)*.

Koć-Januchta, M. M., Schönborn, K. J., Roehrig, C., Chaudhri, V. K., Tibell, L. A., & Heller, H. C. (2022). Connecting concepts helps put main ideas together": cognitive load and usability in learning biology with an AI-enriched textbook. International Journal of Educational Technology in Higher Education, 19(1), 11.

Kocaballi, A. B., Berkovsky, S., Quiroz, J. C., Laranjo, L., Tong, H. L., Rezazadegan, D., ... & Coiera, E. (2019a). The personalisation of conversational agents in health care: a systematic review. *Journal of medical Internet research*, *21*(11), e15360.

Kocaballi, A. B., Laranjo, L., & Coiera, E. (2019b). Understanding and measuring user experience in conversational interfaces. *Interacting with Computers*, *31*(2), 192-207.

Kull, A. J., Romero, M., & Monahan, L. (2021). How may I help you? Driving brand engagement through the warmth of an initial chatbot message. *Journal of Business Research*, *135*, 840-850.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalised engagement marketing. *California Management Review*, *61*(4), 135-155.

Kreutzer, R. T., & Sirrenberg, M. (2020). *Understanding artificial intelligence*. Berlin, Germany: Springer International Publishing.

Kronemann, B., Kizgin, H., Rana, N., & K. Dwivedi, Y. (2023). How AI encourages consumers to share their secrets? The role of anthropomorphism, personalisation, and privacy concerns and avenues for future research. *Spanish Journal of Marketing-ESIC*, *27*(1), 2-19.

Ladkoom, K., and Thanasopon, B. (2020). *Factors Influencing Reuse Intention of e-Payment in Thailand: A Case Study of PromptPay—p*aper presented at the ICEIS (1).

Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., ... & Coiera, E. (2018). Conversational agents in healthcare: a systematic review. *Journal of the American Medical Informatics Association*, *25*(9), 1248-1258.

Laroche, M., Ueltschy, L. C., Abe, S., Cleveland, M., & Yannopoulos, P. P. (2004). Service quality perceptions and customer satisfaction: evaluating the role of culture. Journal of international marketing, 12(3), 58-85.

Lee, K. Y., Sheehan, L., Lee, K., & Chang, Y. (2021). The continuation and recommendation intention of artificial intelligence-based voice assistant systems (AIVAS): the influence of personal traits. Internet Research, 31(5), 1899-1939.

Lin, J. S. C., & Hsieh, P. L. (2007). The influence of technology readiness on satisfaction and behavioral intentions toward self-service technologies. computers in Human Behavior, 23(3), 1597-1615.

Lee, H., Park, N., and Hwang, Y. (2015). A new dimension of the digital divide: Exploring the relationship between broadband connection, smartphone use and communication competence. *Telematics and Informatics, 32*(1), 45-56.

Lee, M., & Ko, E. (2019). The Effect of Customized Chatbot Services on Brand Loyalty toward Luxury Brands. In *2019 Global Fashion Management Conference at Paris* (pp. 828-828).

Lee, J. C., & Lin, R. (2023). The continuous usage of artificial intelligence (AI)-powered mobile fitness applications: the goal-setting theory perspective. Industrial Management & Data Systems, 123(6), 1840-1860.

Lewis, J. R., and Hardzinski, M. L. (2015). Investigating the psychometric properties of the Speech User Interface Service Quality questionnaire. *International Journal of Speech Technology*, 18 (3), 479-487.

Leidner, D. E., & Kayworth, T. (2006). A review of culture in information systems research: Toward a theory of information technology culture conflict. *MIS Quarterly*, 357-399.

Li, M., & Wang, R. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward the brand. *Journal of Retailing and Consumer Services*, *71*, 103209.

Lim, V., Rooksby, M., & Cross, E. S. (2021). Social robots on a global stage: establishing a role for culture during human–robot interaction. *International Journal of Social Robotics*, *13*(6), 1307-1333.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management*, *14*, 21-38.

Lai, C., Wang, Q., Li, X., & Hu, X. (2016). The influence of individual-espoused cultural values on self-directed use of technology for language learning beyond the classroom. *Computers in Human Behavior*, *62*, 676-688.

Li, K. (2023). Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. *Sustainability*, *15*(6), 5221.

Li, C., Pan, R., Xin, H., & Deng, Z. (2020). Research on artificial intelligence customer service on consumer attitude and its impact during online shopping. In *Journal of Physics: Conference Series* (Vol. 1575, No. 1, p. 012192).

Liang, Y., Lee, S. H., & Workman, J. E. (2020). Implementation of artificial intelligence in fashion: Are consumers ready? *Clothing and Textiles Research Journal*, *38*(1), 3-18.

Liao, C., Palvia, P., & Chen, J. L. (2009). Information technology adoption behaviour life cycle: Toward a Technology Continuance Theory (TCT). *International Journal of Information Management*, *29*(4), 309-320.

Liao, H., Proctor, R. W., & Salvendy, G. (2008). Content preparation for cross-cultural e-commerce: a review and a model. *Behaviour & Information Technology*, *27*(1), 43-61.

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). A brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing*, *51*(1), 44-56.

Liew, T. W., Tan, S. M., Tee, J., and Goh, G. G. G. (2021). The effects of designing conversational commerce chatbots with expertise cues. In 2021 14th International Conference on Human System Interaction (HSI) (pp. 1-6). IEEE.

López, G., Quesada, L., & Guerrero, L. A. (2018). Alexa vs. Siri vs. Cortana vs. Google Assistant: A comparison of speech-based natural user interfaces. In *Advances in Human Factors and Systems Interaction: Proceedings of the AHFE 2017 International Conference on Human Factors and Systems Interaction, July 17− 21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8* (pp. 241-250). Springer International Publishing.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937-947.

Lubbe, I., & Ngoma, N. (2021). Useful chatbot experience provides technological satisfaction: An emerging market perspective. *South African Journal of Information Management*, *23*(1), 1-8.

Lv, J., Jiang, X., & Jiang, A. (2022). Application of Virtual Reality Technology Based on Artificial Intelligence in Sports Skill Training. *Wireless Communications and Mobile Computing*, *2022*.

Mackenzie, N., & Knipe, S. (2006). Research dilemmas: Paradigms, methods and methodology. *Issues in educational research*, *16*(2), 193-205.

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A comparison of the theory of planned behaviour and the theory of reasoned action. Personality and Social Psychology Bulletin, 18(1), 3-9.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., ... & Söllner, M. (2019). AI-based digital assistants: Opportunities, threats, and research perspectives. Business & Information Systems Engineering, 61, 535-544.

Malodia, S., Kaur, P., Ractham, P., Sakashita, M., & Dhir, A. (2022). Why do people avoid and postpone the use of voice assistants for transactional purposes? A perspective from decision avoidance theory. Journal of Business Research, 146, 605-618.

Mantelero, A. (2022). The social and ethical components in AI systems design and management. In Beyond Data: Human Rights, Ethical and Social Impact Assessment in AI (pp. 93-137). The Hague: TMC Asser Press.

Mariani, M. M., Hashemi, N., & Wirtz, J. (2023). Artificial intelligence empowered conversational agents: A systematic literature review and research agenda. *Journal of Business Research*, *161*, 113838.

Maier, D., Waldherr, A., Miltner, P., Jähnichen, P., & Pfetsch, B. (2018). Exploring issues in a networked public sphere: Combining hyperlink network analysis and topic modelling. *Social Science Computer Review*, *36*(1), 3-20.

Malodia, S., Islam, N., Kaur, P., & Dhir, A. (2021). Why do people use artificial intelligence (AI)-enabled voice assistants? IEEE Transactions on Engineering Management.

Marinkovic, V., and Kalinic, Z. (2017). Antecedents of customer satisfaction in mobile commerce: Exploring the moderating effect of customisation. Online Information Review.

Martin, A., Nateqi, J., Gruarin, S., Munsch, N., Abdarahmane, I., Zobel, M., & Knapp, B. (2020). An artificial intelligence-based first-line defence against COVID-19: digitally screening citizens for risks via a chatbot. *Scientific reports*, *10*(1), 19012.

Maryanto, R. H., & Kaihatu, T. S. (2021). Customer loyalty is an impact of perceived usefulness to grab users, mediated by customer satisfaction and moderated by perceived ease of use. *Binus Business Review*, *12*(1), 31-39.

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice assistants influence consumer brand engagement?–Examining the role of AI-powered voice assistants in influencing consumer brand engagement. *Journal of Business Research*, *124*, 312-328.

Mekni, M. (2021). An artificial intelligence based virtual assistant using conversational agents. Journal of Software Engineering and Applications, 14(9), 455-473.

Merhi, M. I. (2021). Multi-country analysis of e-commerce adoption: The impact of national culture and economic development. *Pacific Asia Journal of the Association for Information Systems*, *13*(3), 4.

Milhorat, P., Lala, D., Inoue, K., Zhao, T., Ishida, M., Takanashi, K., ... & Kawahara, T. (2019). A conversational dialogue manager for the humanoid robot ERICA. In *Advanced Social Interaction with Agents: 8th International Workshop on Spoken Dialog Systems* (pp. 119-131). Springer International Publishing.

Mimoun, M. S. B., & Poncin, I. (2015). A valued agent: How ECAs affect website customers' satisfaction and behaviours. *Journal of Retailing and Consumer Services*, *26*, 70-82.

Miner, A. S., Laranjo, L., & Kocaballi, A. B. (2020). Chatbots in the fight against the COVID-19 pandemic. *NPJ digital medicine*, *3*(1), 65.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organisational creativity and firm performance. *Information & Management*, *58*(3), 103434.

Mollick, J., Cutshall, R., Changchit, C., & Pham, L. (2023). Contemporary Mobile Commerce: Determinants of Its Adoption. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(1), 501-523.

Mokhlis, S. (2009). Religious differences in some selected aspects of consumer behaviour: a Malaysian study. The Journal of International Management Studies, 4(1), 67-76.

Morgan, D. L. (2014). Pragmatism as a paradigm for social research. *Qualitative Inquiry*, *20*(8), 1045-1053.

Moran-Ellis, J., Alexander, V. D., Cronin, A., Dickinson, M., Fielding, J., Sleney, J., & Thomas, H. (2006). Triangulation and integration: processes, claims and implications. *Qualitative research*, *6*(1), 45-59.

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2021). Engagement with chatbots versus augmented reality interactive technology in e-commerce. *Journal of Strategic Marketing*, *29*(5), 375-389.

Mou, J., Cohen, J., Dou, Y., & Zhang, B. (2020). International buyers' repurchase intentions in a Chinese cross-border e-commerce platform: A valence framework perspective. *Internet Research*, *30*(2), 403-437.

Moon, J. W., & Kim, Y. G. (2001). Extending the TAM for a World-Wide-Web context. Information & Management, 38 (4), 217–230.

Moon, K., & Blackman, D. (2014). A guide to understanding social science research for natural scientists. *Conservation biology*, *28*(5), 1167-1177.

Mukumbang, F. C. (2023). Retroductive theorizing: a contribution of critical realism to mixed methods research. *Journal of Mixed Methods Research*, *17*(1), 93-114.

Mullins, J. K., & Cronan, T. P. (2021). Enterprise systems knowledge, beliefs, and attitude: A model of informed technology acceptance. *International Journal of Information Management*, *59*, 102348.

Nam, K., Dutt, C. S., Chathoth, P., Daghfous, A., & Khan, M. S. (2021). The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges. *Electronic Markets*, *31*, 553-574.

Naeini, F. H. (2012). Usage Pattern, Perceived Usefulness and Ease of Use of Computer Games among Malaysian Elementary School Students. Research Journal of Applied Sciences, Engineering and Technology, 4(23), 5285-5297.

Nagy, S., & Hajdú, N. (2021). Consumer acceptance of the use of artificial intelligence in online shopping: Evidence from Hungary. *Amfiteatru Economic*, *23*(56), 155-173.

Nicolescu, L., & Tudorache, M. T. (2022). Human-computer interaction in customer service: the experience with AI chatbots—a systematic literature review. *Electronics*, *11*(10), 1579.

Nikolenko, S. I., Koltcov, S., & Koltsova, O. (2017). Topic modelling for qualitative studies. *Journal of Information Science*, *43*(1), 88-102.

Nofirda, F. A., & Ikram, M. (2023, June). The Use of Artificial Intelligence on Indonesia Online Shopping Application in Relation to Customer Acceptance. In *Ninth Padang International Conference on Economics Education, Economics, Business and Management, Accounting and Entrepreneurship (PICEEBA 2022)* (pp. 642-651).

Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial intelligence (AI) in banking industry & consumer's perspective. *Sustainability*, *15*(4), 3682.

Nordheim, C. B., Følstad, A., & Bjørkli, C. A. (2019). An initial model of trust in chatbots for customer service—findings from a questionnaire study. *The Journal of Interacting with Computers*, 31(3), 317-335.

Norman, D. (2013). *The Design of Everyday Things: Revised and Expanded Edition*. Basic books.

Nuruzzaman, M., & Hussain, O. K. (2018). A survey on chatbot implementation in the customer service industry through deep neural networks. In 2018 IEEE 15th International Conference on e-Business Engineering (ICEBE) (pp. 54-61). IEEE.

Nunn, N. (2012). Culture and the historical process. Economic History of Developing Regions, 27(sup 1), 108-126.

Oh, K. J., Lee, D., Ko, B., & Choi, H. J. (2017). A chatbot for psychiatric counselling in mental healthcare service based on emotional dialogue analysis and sentence generation. In 2017 18th IEEE International Conference on Mobile Data Management (MDM) (pp. 371-375). IEEE.

Oguntosin, V., & Olomo, A. (2021). Development of an e-commerce chatbot for a university shopping mall. Applied Computational Intelligence and Soft Computing, 2021, 1-14.

Ohk, K., Park, S.-B., and Hong, J.-W. (2015). The influence of perceived usefulness, perceived ease of use, interactivity, and ease of navigation on satisfaction in mobile applications. *Advanced Science and Technology Letters, 84*(2015), 88-92.

Oktavia, T., Agung, C. A., Thalib, D. I., & Rahmanda, Y. D. (2023). An Empirical Study on the Factors Influencing the Attitude and Behaviors Towards Smartphone Voice Assistant Usage. *Journal of System and Management Sciences*, *13*(3), 481-504.

Okuda, T., & Shoda, S. (2018). AI-based chatbot service for the financial industry. *Fujitsu Scientific and Technical Journal*, *54*(2), 4-8.

Onofrei, G., Filieri, R., & Kennedy, L. (2022). Social media interactions, purchase intention, and behavioural engagement: The mediating role of source and content factors. *Journal of Business Research*, *142*, 100-112.

Othman, S., Steen, M., & Fleet, J. (2020). A sequential explanatory mixed methods study design: An example of how to integrate data in a midwifery research project. Journal of Nursing Education and Practice, 11(2), 75-89.

Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: purpose, process, and structure. *Journal of the Academy of Marketing Science*, *46*, 1-5.

Pantano, E., & Di Pietro, L. (2012). Understanding consumer acceptance of technology-based innovations in retailing. *Journal of technology management & innovation*, *7*(4), 1-19.

Park, E. S., & Park, M. S. (2020). Factors of the technology acceptance model for construction IT. *Applied Sciences*, *10*(22), 8299.

Pereira, J., & Díaz, O. (2018). A quality analysis of Facebook Messenger's most popular chatbots. In *Proceedings of the 33rd annual ACM symposium on applied computing* (pp. 2144-2150).

Peña-García, N., Gil-Saura, I., Rodríguez-Orejuela, A., & Siqueira-Junior, J. R. (2020). Purchase intention and purchase behaviour online: A cross-cultural approach. *Heliyon*, *6*(6).

Petter, S. C., & Gallivan, M. J. (2004). Toward a framework for classifying and guiding mixed method research in information systems. In *37th Annual Hawaii International Conference on System Sciences, 2004. Proceedings of the* (pp. 10-pp). IEEE.

Perifanis, N. A., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information*, *14*(2), 85.

Petersson, A. H., Pawar, S., & Fagerstrøm, A. (2023). Investigating the factors of customer experiences using real-life text-based banking chatbot: a qualitative study in Norway. Procedia Computer Science, 219, 697-704.

Pei, Z., & Zhenxiang, Z. (2006). A framework for personalized service website based on TAM. In 2006 International Conference on Service Systems and Service Management (Vol. 2, pp. 1598-1603). IEEE.

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human, but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, *38*(4), 626-642.

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, *57*, 102207.

Pinsky, L. (1951). Do machines think about machines thinking? *The Turing Test: Verbal Behavior as the Hallmark of Intelligence*, *143*.

Polit, D. F., & Beck, C. T. (2010). Generalization in quantitative and qualitative research: Myths and strategies. *International journal of nursing studies*, *47*(11), 1451-1458.

Polkosky, M. D., & Lewis, J. R. (2003). Expanding the MOS: Development and psychometric evaluation of the MOS-R and MOS-X. *International Journal of Speech Technology*, *6*(2), 161-182.

Poncet, A., Courvoisier, D. S., Combescure, C., & Perneger, T. V. (2016). Normality and sample size do not matter in selecting an appropriate statistical test for two-group comparisons. *Methodology*.

Prasad, V. A., & Ranjith, R. (2020). Intelligent chatbot for lab security and automation. In *2020, the 11th International Conference on Computing, Communication and Networking Technologies (ICT)* (pp. 1-4). IEEE.

Purwanto, E., & Loisa, J. (2020). The intention and use behaviour of the mobile banking system in Indonesia: UTAUT Model. *Technology Reports of Kansai University*, *62*(06), 2757-2767.

Rana, M., & Arora, N. (2022). How does social media advertising persuade? An investigation of the moderation effects of corporate reputation, privacy concerns and intrusiveness. *Journal of Global Marketing*, *35*(3), 248-267.

Rakhra, M., Gopinadh, G., Addepalli, N. S., Singh, G., Aliraja, S., Reddy, V. S. G., & Reddy, M. N. (2021). E-commerce assistance with a smart chatbot using artificial intelligence. In *2021 2nd International Conference on Intelligent Engineering and Management (ICIEM)* (pp. 144-148). IEEE.

Radziwill, N. M., & Benton, M. C. (2017). Evaluating the quality of chatbots and intelligent conversational agents. *arXiv preprint arXiv:1704.04579*.

Ramayah, T., Yeap, J. A., Ahmad, N. H., Halim, H. A., & Rahman, S. A. (2017). Testing a confirmatory model of Facebook usage in SmartPLS using consistent PLS. *International Journal of Business and Innovation*, *3*(2), 1-14.

Rawlings, C. M. (2020). Cognitive authority and the constraint of attitude change in groups. *American Sociological Review*, *85*(6), 992-1021.

Ranoliya, B. R., Raghuwanshi, N., & Singh, S. (2017). Chatbot for university-related FAQs. In *2017 International Conference on Advances in Computing, Communications, and Informatics (ICACCI)* (pp. 1525-1530). IEEE.

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance. *Journal of Retailing and Consumer Services*, *56*, 102176.

Rezaei, S., & Valaei, N. (2017). Branding in a multichannel retail environment: Online stores vs app stores and the effect of product type. *Information Technology & People*, *30*(4), 853-886.

Rhee, C. E., & Choi, J. (2020). Effects of personalisation and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. *Computers in Human Behavior*, *109*, 106359.

Rindfleisch, A., Malter, A. J., Ganesan, S., & Moorman, C. (2008). Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. *Journal of marketing research*, *45*(3), 261-279.

Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modelling in HRM research. *The International Journal of Human Resource Management*, *31*(12), 1617-1643.

Riquelme, L. F., and Rosas, J. (2014). Multicultural perspectives: The road to cultural competence. Language development: Foundations, processes, and clinical applications, 255-256.

Roy, R., & Naidoo, V. (2021). Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation. *Journal of Business Research*, *126*, 23-34.

Roh, T., Park, B. I., & Xiao, S. S. (2023). Adoption of AI-enabled Robo-advisors in Fintech: Simultaneous Employment of UTAUT and the Theory of Reasoned Action. *Journal of Electronic Commerce Research*, *24*(1), 29-47.

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review*, *33*(1), 100925.

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services*, *68*, 103059.

Saniuk, S., Grabowska, S., & Gajdzik, B. (2020). Personalisation of products in the Industry 4.0 concept and its impact on achieving a higher level of sustainable consumption. *Energies*, *13*(22), 5895.

Sakshaug, J. W., Hülle, S., Schmucker, A., & Liebig, S. (2017, August). Exploring the effects of interviewer-and self-administered survey modes on record linkage consent rates and bias. In *Survey Research Methods* (Vol. 11, No. 2, pp. 171-188).

Sarkar, S., Chauhan, S., & Khare, A. (2020). A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management*, *50*, 286-301.

Sarica, S., & Luo, J. (2021). Stopwords in technical language processing. *Plos one*, *16*(8), e0254937.

Said, M., Ramayah, T., & Al Salihi, S. M. R. (2022). Modelling Chatbots Adoption for Online Shopping Amidst the Covid-19 Pandemic. *Global Business and Management Research*, *14*(4s), 329-338.

Sánchez-Díaz, X., Ayala-Bastidas, G., Fonseca-Ortiz, P., & Garrido, L. (2018). A knowledge-based methodology for building a conversational chatbot as an intelligent tutor. In *Advances in Computational Intelligence: 17th Mexican International Conference on Artificial Intelligence, MICAI 2018, Guadalajara, Mexico, October 22–27, 2018, Proceedings, Part II 17* (pp. 165-175). Springer International Publishing.

Song, R., Moon, S., Chen, H., & Houston, M. B. (2018). When marketing strategy meets culture: The role of culture in product evaluations. Journal of the Academy of Marketing Science, 46, 384-402.

Straub, D., Loch, K., Evaristo, R., Karahanna, E., & Srite, M. (2002). Toward a theory-based measurement of culture. Journal of Global Information Management (JGIM), 10(1), 13-23.

Sano, A. V. D., Imanuel, T. D., Calista, M. I., Nindito, H., & Condrobimo, A. R. (2018, September). The application of AGNES algorithm to optimise knowledge base for tourism chatbot. In *2018 International Conference on Information Management and Technology (ICIMTech)* (pp. 65-68). IEEE.

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson education.

Sciarelli, M., Prisco, A., Gheith, M. H., & Muto, V. (2022). Factors affecting the adoption of blockchain technology in innovative Italian companies: an extended TAM approach. *Journal of Strategy and Management*, *15*(3), 495-507.

Schanke, S., Burtch, G., & Ray, G. (2021). Estimating the impact of “humanizing” customer service chatbots. *Information Systems Research*, *32*(3), 736-751.

Selamat, M. A., & Windasari, N. A. (2021). Chatbot for SMEs: Integrating customer and business owner perspectives. *Technology in Society*, *66*, 101685.

Serban, I. V., Lowe, R., Henderson, P., Charlin, L., & Pineau, J. (2015). A survey of available corpora for building data-driven dialogue systems. *arXiv preprint arXiv:1512.05742*.

Serrano-Malebran, J., & Arenas-Gaitan, J. (2021). When does personalisation work on social media? A posteriori segmentation of consumers. Multimedia Tools and Applications, 80, 36509-36528.

Setiaji, B., & Wibowo, F. W. (2016). Chatbot using knowledge in database: human-to-machine conversation modelling. In *2016, 7th International Conference on Intelligent Systems, Modelling, and Simulation (ISMS)* (pp. 72-77). IEEE.

Septianto, F., Kemper, J. A., & Choi, J. J. (2020). The power of beauty? The interactive effects of awe and online reviews on purchase intentions. *Journal of Retailing and Consumer Services*, *54*, 102066.

Sfenrianto, S., & Vivensius, G. (2020). Analysis of factors influencing customer experience of e-commerce users in Indonesia through the application of Chatbot technology. *J. Theor. Appl. Inf. Technol*, *98*(7), 953-962.

Sharma, A., & Jhamb, D. (2020). Changing consumer behaviours towards online shopping-an impact of COVID-19. *Academy of Marketing Studies Journal*, *24*(3), 1-10.

Shannon-Baker, P. (2016). Making paradigms meaningful in mixed methods research. *Journal of mixed methods research*, *10*(4), 319-334.

Shiau, W. L., Yuan, Y., Pu, X., Ray, S., & Chen, C. C. (2020). Understanding fintech continuance: perspectives from self-efficacy and ECT-IS theories. *Industrial Management & Data Systems*, *120*(9), 1659-1689.

Shin, D. H. (2010). Analysis of online social networks: A cross-national study. *Online Information Review*, *34*(3), 473-495.

Shneiderman, B. (2020). Bridging the gap between ethics and practice: guidelines for reliable, safe, and trustworthy human-centred AI systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, *10*(4), 1-31.

Sheehan, B., Jin, H. S., and Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, 115, 14-24.

Sidi, F., Panahy, P. H. S., Affendey, L. S., Jabar, M. A., Ibrahim, H., & Mustapha, A. (2012, March). Data quality: A survey of data quality dimensions. In *2012 International Conference on Information Retrieval & Knowledge Management* (pp. 300-304). IEEE.

Simpson, S. H. (2015). Creating a data analysis plan: What to consider when choosing statistics for a study. *The Canadian journal of hospital pharmacy*, *68*(4), 311.

Singh, C., Dash, M. K., Sahu, R., & Kumar, A. (2024). Investigating the acceptance intentions of online shopping assistants in E-commerce interactions: Mediating role of trust and effects of consumer demographics. Heliyon, 10(3).

Sindermann, C., Yang, H., Elhai, J. D., Yang, S., Quan, L., Li, M., & Montag, C. (2022). Acceptance and fear of Artificial Intelligence: Associations with personality in a German and a Chinese sample. Discover Psychology, 2(1), 8.

Siebra, C., Correia, W., Penha, M., Macedo, J., Quintino, J., Anjos, M., ... & Santos, A. L. (2018). Virtual assistants for mobile interaction: A review from the accessibility perspective. In *Proceedings of the 30th Australian Conference on Computer-Human Interaction* (pp. 568-571).

Srivastava, M., & Kaul, D. (2016). Exploring the link between customer experience–loyalty–consumer spend. *Journal of Retailing and Consumer Services*, *31*, 277-286.

Srite, M., & Karahanna, E. (2006). The role of espoused national cultural values in technology acceptance. *MIS Quarterly*, 679-704.

Skjerve, H., Braaum, L. E., Goth, U. S., & Sørensen, A. (2023). Using Simulations to Help Public Health Students Overcome Language Barriers for Better Health Outcomes. *International Journal of Environmental Research and Public Health*, *20*(13), 6259.

Sormin, E., Julianti, K., Nadeak, B., & Naibaho, L. (2019). Use of construction inquiry learning model to improve the interest of learning students grade XI SMA Angkasa 2 in colloid materials. *PEOPLE International Journal of Social Sciences*, *5*(2), 908-917.

Sobti, N. (2019). Impact of demonetisation on the diffusion of mobile payment service in India: Antecedents of behavioural intention and adoption using extended UTAUT model. *Journal of Advances in Management Research*, *16*(4), 472-497.

Song, X., Yang, S., Huang, Z., & Huang, T. (2019). The application of artificial intelligence in electronic commerce. In *Journal of Physics: Conference Series* (Vol. 1302, No. 3, p. 032030). IOP Publishing.

Srinivasan, S. S., Anderson, R., and Ponnavolu, K. (2002). Customer loyalty in e-commerce: an exploration of its antecedents and consequences. *Journal of Retailing, 78* (1), 41-50.

Subedi, D. (2016). Explanatory sequential mixed method design as the third research community of knowledge claim. *American Journal of Educational Research*, *4*(7), 570-577.

Sudaryanto, M. R., Hendrawan, M. A., & Andrian, T. (2023). The Effect of Technology Readiness, Digital Competence, Perceived Usefulness, and Ease of Use on Accounting Students Artificial Intelligence Technology Adoption. In *E3S Web of Conferences* (Vol. 388). EDP Sciences.

Suhel, S. F., Shukla, V. K., Vyas, S., & Mishra, V. P. (2020, June). Conversation to automation in banking through chatbot using artificial machine intelligence language. In *2020 8th International Conference on Reliability, Infocom Technologies and Optimisation (trends and future directions) (ICRITO)* (pp. 611-618). IEEE.

Suresh, T. P., Yong, P. L., Chyi, Y. S., & Musa, R. (2023). Connecting with Generation Z: Consumer Acceptance of the Use of Artificial Intelligence in Online Shopping. *Journal of Entrepreneurship and Business (JEB)*, *11*(1), 56-68.

Sutherland, I., & Kiatkawsin, K. (2020). Determinants of the guest experience in Airbnb: a topic modelling approach using LDA. *Sustainability*, *12*(8), 3402.

Svikhnushina, E., Placinta, A., & Pu, P. (2021). User expectations of conversational chatbots based on online reviews. In *Designing Interactive Systems Conference 2021* (pp. 1481-1491).

Synnott, J., Harkin, M., Horgan, B., McKeown, A., Hamilton, D., McAllister, D., ... & Nugent, C. (2020). The digital skills, experiences and attitudes of the Northern Ireland social care workforce toward technology for learning and development: Survey study. *JMIR medical education*, *6*(2), e15936.

Syarova, L. (2022). Chatbot usage in e-retailing and the effect on customer satisfaction.

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in science education*, *48*, 1273-1296.

Tabet, S., Bhogaraju, P., & Ash, D. (2000). Using XML as a Language Interface for AI Applications. In *Pacific Rim International Conference on Artificial Intelligence* (pp. 103-110). Berlin, Heidelberg: Springer Berlin Heidelberg.

Tahar, A., Riyadh, H. A., Sofyani, H., & Purnomo, W. E. (2020). Perceived ease of use, perceived usefulness, perceived security and intention to use e-filing: The role of technology readiness. *The Journal of Asian Finance, Economics and Business (JAFEB)*, *7*(9), 537-547.

Tan, P. K., & Lim, C. M. (2023). Factors That Affect User Satisfaction of Using E-Commerce Chatbot: A Study on Generation Z. *International Journal of Business and Technology Management*, *5*(1), 292-303.

Tandi Lwoga, E., & Questier, F. (2014). Faculty adoption and usage behaviour of open access scholarly communication in health science universities. *New Library World*, *115*(3/4), 116-139.

Tang, W. P., Chan, C. W., So, W. K., & Leung, D. Y. (2014). Web-based interventions for caregivers of cancer patients: a review of the literature. *Asia-Pacific journal of oncology nursing*, *1*(1), 9-15.

Teo, T., & Huang, F. (2019). Investigating the influence of individually espoused cultural values on teachers' intentions to use educational technologies in Chinese universities. Interactive Learning Environments, 27 (5-6), pp. 813-829.

Teo, T., Lee, C. B., Chai, C. S., & Wong, S. L. (2009). Assessing the intention to use technology among pre-service teachers in Singapore and Malaysia: A multigroup invariance analysis of the Technology Acceptance Model (TAM). *Computers & Education*, *53*(3), 1000-1009.

Teodorescu, D., Aivaz, K. A., Vancea, D. P. C., Condrea, E., Dragan, C., & Olteanu, A. C. (2023). Consumer Trust in AI Algorithms Used in E-Commerce: A Case Study of College Students at a Romanian Public University. *Sustainability*, *15*(15), 11925.

Toader, D. C., Boca, G., Toader, R., Măcelaru, M., Toader, C., Ighian, D., & Rădulescu, A. T. (2019). The effect of social presence and chatbot errors on trust. *Sustainability*, *12*(1), 256.

Triandis, H. C. (2015). Raised in a collectivist culture, one may become an individualist. In *Working at the Interface of Cultures* (pp. 38-46). Routledge.

Tsai, W. H. S., Liu, Y., & Chuan, C. H. (2021). How chatbots' social presence communication enhances consumer engagement: the mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing*, *15*(3), 460-482.

Uprichard, E., & Dawney, L. (2019). Data diffraction: Challenging data integration in mixed methods research. *Journal of mixed methods research*, *13*(1), 19-32.

Uzir, M. U. H., Bukari, Z., Al Halbusi, H., Hock, R. L. T., Wahab, S. N., Rasul, T., ... & Eneizan, B. (2023). Applied artificial intelligence: Acceptance-intention-purchase and satisfaction on smartwatch usage in a Ghanaian context. *Heliyon*.

Uysal, E., Alavi, S., & Bezençon, V. (2022). Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features. *Journal of the Academy of Marketing Science*, *50*(6), 1153-1175.

Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., & Torous, J. B. (2019). Chatbots and conversational agents in mental health: a review of the psychiatric landscape. *The Canadian Journal of Psychiatry*, *64*(7), 456-464.

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? *Computers in Human Behavior*, *98*, 150-157.

Venkatesh, V., Speier-Pero, C., & Schuetz, S. (2022). Why do people shop online? A comprehensive framework of consumers' online shopping intentions and behaviours. *Information Technology & People*, *35*(5), 1590-1620.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 21-54.

Wang, C., Ahmad, S. F., Ayassrah, A. Y. B. A., Awwad, E. M., Irshad, M., Ali, Y. A., ... & Han, H. (2023a). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. *Heliyon*.

Wang, S., Menon, S., Long, T., Henderson, K., Li, D., Crowston, K., ... & Chilton, L. B. (2023b). ReelFramer: Co-creating News Reels on social media with Generative AI. *arXiv preprint arXiv:2304.09653*.

Weizenbaum, J. (1966). ELIZA—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, *9*(1), 36-45.

Whitley, E., & Ball, J. (2002). Statistics review 4: sample size calculations. *Critical care*, 6 (4), 1–7.

Wilkinson, D., Alkan, Ö., Liao, Q. V., Mattetti, M., Vejsbjerg, I., Knijnenburg, B. P., & Daly, E. (2021). Why or why not? The effect of justification styles on chatbot recommendations. *ACM Transactions on Information Systems (TOIS)*, *39*(4), 1-21.

Woolley, C. M. (2009). Meeting the mixed methods challenge of integration in a sociological study of structure and agency. *Journal of Mixed Methods Research*, *3*(1), 7-25.

Wu, F. C., Hong, O. N.-J., Trappey, A. J., & Trappey, C. V. (2020). *VR-enabled chatbot system supporting transformer mass-customization services.* Paper presented at the 27th ISTE International Conference on Transdisciplinary Engineering, TE 2020.

Xie, Q., Tan, D., Zhu, T., Zhang, Q., Xiao, S., Wang, J., ... & Yi, P. (2019). Chatbot application on cryptocurrency. In *2019 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)* (pp. 1-8).

Xiao, L., Guo, F., Yu, F., & Liu, S. (2019). The effects of online shopping context cues on consumers' purchase intention for cross-border E-Commerce sustainability. *Sustainability*, *11*(10), 2777.

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. International Journal of Hospitality Management, 43, 1-12.

Xiong, Y., Shi, Y., Pu, Q., & Liu, N. (2024). More trust or more risk? User acceptance of artificial intelligence virtual assistant. Human Factors and Ergonomics in Manufacturing & Service Industries, 34(3), 190-205.

Xiong, Y. (2022). The impact of artificial intelligence and digital economy consumer online shopping behaviour on market changes. *Discrete Dynamics in Nature and Society*, *2022*.

Yamaguchi, H., Mozgovoy, M., & Danielewicz-Betz, A. (2018). A Chatbot Based On AIML Rules Extracted From Twitter Dialogues. In *FedCSIS (Communication Papers)* (pp. 37-42).

Yang, B., Liu, Y., Liang, Y., & Tang, M. (2019). Exploiting user experience from online customer reviews for product design. *International Journal of Information Management*, *46*, 173-186.

Yazici, B., & Yolacan, S. (2007). A comparison of various tests of normality. *Journal of Statistical Computation and Simulation*, *77*(2), 175-183.

Yen, Y. S. (2023). Channel integration affects usage intention in food delivery platform services: the mediating effect of perceived value. *Asia Pacific Journal of Marketing and Logistics*, *35*(1), 54-73.

Yin, J., & Qiu, X. (2021). AI technology and online purchase intention: Structural equation model based on perceived value. *Sustainability*, *13*(10), 5671.

Yi, M. Y., Fiedler, K. D., & Park, J. S. (2006). Understanding the role of individual innovativeness in the acceptance of IT-based innovations: Comparative analyses of models and measures. Decision sciences, 37(3), 393-426.

Youn, S. Y., & Lee, K. H. (2019). Proposing value-based technology acceptance model: Testing on paid mobile media service. *Fashion and textiles*, *6*(1), 1-16.

Zaiţ, A., & Bertea, P. S. P. E. (2011). Methods for testing discriminant validity. *Management & Marketing Journal*, *9*(2), 217-224.

Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking*, *21*(8), 491-497.

Zhang, S., Meng, Z., Chen, B., Yang, X., & Zhao, X. (2021). Motivation, Social Emotion, and the Acceptance of Artificial Intelligence Virtual Assistants—Trust-Based Mediating Effects. *Frontiers in Psychology*, *12*, 728495.

Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. International Journal of Information Management, 57, 102304.

Zhang, K. Z., Zhao, S. J., Cheung, C. M., & Lee, M. K. (2014). Examining the influence of online reviews on consumers' decision-making: A heuristic–systematic model. *Decision Support Systems*, *67*, 78-89.

Zierau, N., Hausch, M., Bruhin, O., & Söllner, M. (2020). Towards Developing Trust-Supporting Design Features for AI-Based Chatbots in Customer Service. In *ICIS* (Vol. 2020, pp. 1-9).

Zimmermann, R., Mora, D., Cirqueira, D., Helfert, M., Bezbradica, M., Werth, D., ... & Auinger, A. (2023). Enhancing brick-and-mortar store shopping experience with an augmented reality shopping assistant application using personalised recommendations and explainable artificial intelligence. *Journal of Research in Interactive Marketing*, *17*(2), 273-298.

Zhou, L., Dai, L., & Zhang, D. (2007). Online shopping acceptance model critical survey of consumer factors in online shopping. *Journal of Electronic Commerce Research*, *8*(1).

Appendices

Appendix A. Factors Questions of the Survey Questionnaire

- Please tell us the extent to which you agree with the following statements assessing the chatbot as a useful tool.

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
The chatbot provides useful information.	○	○	○	○	○
The chatbot provides sufficient content.	○	○	○	○	○
The chatbot makes it easy to find the content required.	○	○	○	○	○

-Please tell us the extent to which you agree with the following statements about the chatbot on its ease of use.

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
Learning to use the chatbot is easy for me.	○	○	○	○	○
The interaction with the chatbot is clear and understandable.	○	○	○	○	○
I would find it easy to use the chatbot to search for what I want.	○	○	○	○	○

-Please tell us the extent to which you agree with the following statements assessing the chatbot for its ability to provide customized services (customized search recommendations, product, and email sales notifications)

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
If I changed to another brand, the products and services would not be as customized as I have now.	○	○	○	○	○
The chatbot offers products and services that would be difficult for me to find.	○	○	○	○	○
I feel that using the chatbot and transacting with it may meet my personal needs.	○	○	○	○	○
The chatbot provides information about products according to my preferences.	○	○	○	○	○

-Please tell us the extent to which you agree with the following statements assessing the communication competence of the chatbot.

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
My interactions with the chatbot can be more productive than face-to-face interactions with in-store personnel.	○	○	○	○	○
Using chatbots can be more efficient than other forms of communication.	○	○	○	○	○
Chatbots can save a tremendous amount of time.	○	○	○	○	○

- Please tell us the extent to which you agree with the following statements based on your attitude towards chatbot usage in general.

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
I would have positive feelings towards using the chatbot.	○	○	○	○	○
The thought of browsing a product from the chatbot is appealing to me	○	○	○	○	○
It would be a good idea to find the right product using the chatbot.	○	○	○	○	○

- Please tell us the extent to which you agree with the following statements about your intention to use the chatbot in the future.

	Strongly agree (1)	Agree (2)	Neutral (3)	Disagree (4)	Strongly disagree (5)
I will use the chatbot on a regular basis in the future.	○	○	○	○	○
I will frequently use the chatbot in the future.	○	○	○	○	○
I will strongly recommend others to use chatbot.	○	○	○	○	○

Appendix B. AI Assistant Interaction Simulations